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DEVELOPMENT OF A PROCEDURE FOR MAKING INSPECTION PLANS FOR CORRODING OIL AND GAS PIPING

Master Thesis by

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SUMMARY

The degradation of topsides process piping on an offshore platform carrying oil and gas can result in undesirable events like bursts and leakages. In order to manage the challenges arising from such failures, the piping is regularly inspected using different types of Non Destructive Testing (NDT) methods. Since this piping has different configurations and is often located in places that are difficult to access, the associated costs of these activities are quite high. To support the decision-making on the development of an effective and efficient inspection programme, Risk-Based Inspection (RBI) analysis is often used. Based on the recommendations of the RBI analysis, the inspection is carried out and the results of the inspection are then reinvested into the inspection management programme to update the analysis.

This thesis presents a methodology based on Bayesian updating to formally ensure that experience and knowledge are used in a systematic way, when deciding how much needs to be inspected in order to be convinced that the corrosion group of components does not contain any significant corrosion. It is expected that the implementation of the methodology will improve the inspection management by providing a systematic tool to incorporate the inspection results, provide traceability and reveal critical assumptions. This thesis will also present a method for how to evaluate and communicate different uncertainty factors.

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CHAPTER 1

INTRODUCTION

1.1 Background

Inspection management is one of the important tasks in an offshore installation, because several accidents have taken places due to insufficient inspection management and corrosion of critical equipment. Topside piping is therefore regularly inspected to ensure a safe and reliable operation. This inspection planning is often based on the concept of Risk-Based Inspection, RBI. This analysis will help in identifying areas where there are high consequences if a leak or rupture occurs and where there exists a probability of failure, PoF.

Deciding the probability of failure is a challenging task. Sometimes the PoF is based on expert judgements, but is often calculated using established degradation models, but these models often turn out to be quite conservative. Inspections are therefore used to reduce the probability of failure. The inspection of topside equipment is expensive to carry out, and should consequently be kept to a minimum. This raises the important question, how much is necessary to inspect in order to reduce the risk to an acceptable level? What should this decision be based on, and how can the decision be justified? Should it only rely on expert opinions or is it possible to find methods that can be used as decision support?

The purpose of the RBI analysis is to find an effective inspection plan, which intends to maximise the availability of assets at an acceptable cost without compromising on safety. The inspection plans today are often quite conservative, leading to high inspection costs. Still, knowledge can reduce the uncertainty, and inspections are therefore required. However, when do we know enough to stop inspecting?

1.2 Aim of the Thesis

The aim of this thesis is to give an answer to the above-mentioned question: when do we know enough about the piping's condition to stop inspection? In other words, how much is it necessary to inspect in order to feel secure about the condition of the piping? This thesis will develop a method that can be used as decision support when trying to answer this question. The method used will also secure a systematic treatment of new inspection results and combine those with all the available background knowledge.

1.3 The Scope of Work

This thesis will look into the use of Bayesian updating as decision support. This is a method that can be used to decide the number of inspected hot spots necessary to achieve the required confidence of the condition in a large corrosion group. In order to apply this method a flow chart will be presented.

The need for an extended RBI analysis, where uncertainty factors are identified and evaluated, will be presented.

The second part of the thesis presents the strengths and weaknesses of Bayesian updating and guidelines to successful (right) usage of the method.

1.4 Limitations

The main limitation of this method is the introduction of a parameter θ, which can only be given a meaningful interpretation as long as the number of hot spots in a corrosion group is high or it is possible to imagine a large number of hot spots. This method focuses on deciding whether or not significant corrosion is present; if significant corrosion is present, other methods should be used to decide the need for measures or more inspections.

1.5 Organization of the Thesis

This thesis contains five chapters with several different sub-chapters. The first chapter gives an introduction to the thesis, the background, aim, scope and terminology. The next chapter will present the knowledge which is necessary, in order to understand the procedure introduced in Chapter Three. Chapter two will also give an introduction to uncertainty factors, and how they can be treated. Chapter Four will provide a discussion regarding the procedure presented in Chapter Three, while Chapter Five will give a short conclusion.

1.6 Terminology

The terminology used in this thesis is in accordance with the terminology presented in Aven (2008, 2010).

Risk definition:	Combination of an event A, its consequences C, and the uncertainty U, related to the event and its consequences (Aven, 2008).

Risk description:	(A,C,U,P,S,K). The event A, the different consequences C, the uncertainties attached to both A and C, the probabilities P (knowledge-based) used to describe U, a sensitivity S to see how variation in different input conditions and assumptions changes the risk picture, and given the background knowledge K. (Aven and Flage, 2009). See Section 2.2.3 for an alternative description.
Uncertainty:	Lack of knowledge about a phenomenon.
Aleatory uncertainty:	Variation of quantities in a population; for Bayesians, known as **variation**.
Epistemic uncertainty:	Uncertainty regarding a phenomenon due to lack of knowledge. Bayesians consider this as the only type of uncertainty (Aven, 2010).
Probabilities:	Knowledge-based judgement about uncertainties, comparing the uncertainty of an event/consequence with drawing a blue ball, p, out of an urn containing p% blue balls (Aven, 2010). Also known as knowledge-based probability.
Chance:	The fraction of “successes” if the experiment is repeated infinitely under the same conditions.
Expert:	Person with in-depth knowledge about a process or phenomenon.
Confidence interval:	A 90% confidence interval [a,b] for a parameter, θ, means that the parameter will be in the interval in 90% of the cases if the experiment can be repeated infinitely.
Credibility interval:	A 90% credibility interval [θ_1, θ_2] for a parameter, θ, means that the interval contains θ with a probability equal to 0.90. In other words, $P(\theta_1 \leq \theta \leq \theta_2) = 0.90$.
Prediction interval:	A 90% prediction interval [a, b] for a quantity, X, means that the interval contains X with a probability equal to 0.90. In other words, $P(a \leq X \leq b) = 0.90$ where X is an observable quantity.
Exchangeable sequence:	A sequence of random quantities, where their joint distribution functions are independent of the order of the quantities in the sequence (Bernardo and Smith, 2000).
Event:	The occurrence of a particular set of circumstances (ISO, 2002).

Significant corrosion: Measurable corrosion with potential to threaten the equipment's integrity.

CHAPTER 2

BACKGROUND INFORMATION

2.1 Definitions and Explanations

2.1.1 Risk and Decision Making

Decisions are made every day, some of them more thought-through than others. Some decisions are easy, while others are more complex. An easy decision can be identified as a decision problem where the consequences of the different decisions are known and you have one solution that is clearly the best compared to the others. On the other side are the more complex decision problems: decisions where there are no clear consequences and where uncertainties also become a part of the problem. Risk management becomes an important task when dealing with decision making under uncertainty.

When choosing between different decisions one will have to consider the event (A), the event's different consequences (C) and the uncertainties (U) attached to both A and C. This is in accordance with the risk definition presented in Aven (2008) and will be used throughout this thesis.

In most situations people tend to prefer known consequences. Consider, for example, the case where you can choose to get 1000 dollars for sure or you can choose to participate in a game where you have the possibility of winning 5000 dollars with a chance of 0.4 or nothing otherwise. Some of us, the risk averse, will choose 1000 dollars, while others, risk seekers, prefer the game where they can win 5000 dollars. Let us say that you get the opportunity to participate in a game where you can win 5000 dollars with a chance 0.9, but you have to pay 1000 dollars to be allowed to play.

This seems like a game where you are almost certain to win, but what if the game is not fair? You may wonder why anyone should give you money. Uncertainty becomes a part of your decision problem: to play or not to play? You will seek more information in order to reduce the uncertainty, and hopefully end up with the "best" solution, a solution which is beneficial. Has anyone played this game before? What happened with them? Will you be allowed to try the game before you decide to play? Can you trust the person offering the game, and so on?

This need for information will always be present when dealing with decision making under uncertainty. As will be the case in this thesis, when do we have enough information to feel secure about the conditions in the decision problem? In the example above, necessary information could have come from people that have already played the game or the first impression you get of the guy offering the game, and it may be easier to make a decision.

2.1.2 Reducing Uncertainty

Probabilities are often used to express uncertainty, but there exist two different frameworks for probability. There is a strong need for an explanation of the two different types. The classical viewpoint sees probability as a relative frequency, meaning that P(A) is the fraction of times A occurs if the situation can be repeated under the same conditions infinitely.

Another approach to probability, the one that will be adopted in this thesis, is called knowledge-based probability. This probability compares the degree of uncertainty with a standard. For example, to compare the uncertainty of an event/consequence with drawing a blue ball, out of an urn containing p*100 % blue balls (Aven, 2010), p is then the probability.

Before going further, it is necessary to address the ongoing discussion regarding the meaning of probability. Statisticians that see probability as a knowledge-based judgement about uncertainty are known as Bayesians, while statisticians that address probability as a relative frequency are called frequentists. The main difference between these two views is the possibility of assigning a probability to a single event.

For frequentists, it is impossible and meaningless to talk about the probability of a single event, as they will say that this does not have anything to do with the mathematical theory of probability; see Leda Cosmides and John Tooby (1996). Frequentists say that a single event can not have a probability as probability always refers to a population (like Norwegians or a large amount of marbles).

For Bayesians, on the other hand, probability exists for single events. This is due to the fact that they see probability as a personal expression of uncertainty regarding the occurrence of an event given the available knowledge. Some degree of knowledge regarding the occurrence of an event will always exist.

Leda Cosmides and John Tooby (1996), have in their introduction to “Are humans good intuitive statisticians after all? Rethinking some conclusions from the literature on judgement under uncertainty”, presented the differences between what they call subjective probabilities (also known as knowledge-based probabilities) and objective frequencies. I refer to this article for an easy explanation for why Bayesians and frequentists disagree. The advantages of being a Bayesian will be discussed in Section 3.3.

2.1.3 Epistemic and Aleatory Uncertainty

Uncertainties are often divided into epistemic and aleatory uncertainty. Epistemic uncertainty is uncertainty caused by lack of knowledge, while aleatory uncertainties are due to the variation within a population. Aleatory uncertainties are present because the system that is being studied can behave differently, and these uncertainties are therefore a part of the system. An example may be smokers; you are interested in the average number of smokers in each class at a school. Smokers can be considered as your system (population), and the number of smokers in each class can be different from the average for the whole school. This variation between the average and the number of smokers in one class is referred to as aleatory uncertainty.

Epistemic uncertainties are the only uncertainties that exist when adopting the knowledge-based approach to probability, meaning that the only uncertainties that exist are due to lack of knowledge; variation in a population/system is just called variation. Uncertainty is then something that can be reduced by increasing the knowledge about the phenomena that are being studied. Variation can not be reduced as it is a part of the phenomena that are being studied.

When doing inspection planning, uncertainties are always present. These uncertainties are attached to the consequences, the occurrence and the location of a leak. There are several different factors that influence these uncertainties. The consequences of a leak have to do with nearby equipment, the content of the piping, the pressure and temperature of the content, size of the leak, if ignition sources are present, the effectiveness of implemented measures like firewalls, blast walls, fire water and so on.

2.1.4 Value of Information

When doing research, new information may become available. This new relevant information may change the direction of the research and influence the final conclusion. It is therefore important to make sure that new information is processed in a systematic way so that all relevant information is considered before a decision is made. Systematic coherent treatment of inspection results can be achieved by Bayesian updating. Coherent treatment means that the decision process is logical; an example of coherent behaviour can be that alternative a is better than b, which is better than c. Then alternative a is also better than c; see Lindley (1985).

A well-known concept in risk management is the ALARP principle, meaning that one should reduce risk to an as low as reasonably practicable level. In the context of inspection management, ALARP will mean that the risk attached to a leak should be reduced to a level which is as low as reasonably practicable. Because risk can be defined as the combination of the event, a leak, the consequences, like fire or explosion and the different uncertainties attached to both the occurrence of the event and the different consequences. Consequently, there are three different areas where measures can be implemented to reduce the risk. Measures to reduce the probability of the occurrence of the event - for a leak, thicker material, corrosion inhibitors and more - can be used. Fire and explosion walls can be used to reduce the consequences of a leak, while knowledge can be used to reduce the uncertainty. Knowledge can be found when performing inspections or by comparing with similar situations and so on, but when do we know enough to stop inspecting?

The risk can be considered as high as long as there are large uncertainties attached to both the occurrence and the consequence of a leak. Not all the uncertainties can be expressed by a probability. When dealing with corrosion, the uncertainty is mostly associated with the actual state of the piping. The consequences are often quite clear, and models are developed to calculate the corrosion rate and thereby be able to predict the state of the piping. Still, it is important not to forget the different uncertainty factors related to the background knowledge; this will be described further in Section 2.2.2.

Nevertheless, inspectors get surprises, both when they find corrosion which was not expected and the other way around. The need for inspections is therefore clear, as it increases the knowledge about the piping condition and thereby reduces the uncertainty. Inspections give more available information and it becomes easier to predict the condition of the remaining part of the piping in the corrosion group. Further, inspections increase the knowledge and reduce some of the original uncertainty factors; see Section 2.1.2.

Still, it is important to remember that inspections only increase the knowledge as long as the inspection method used is suitable. With a high chance of detection (POD), the fraction of times the inspection methods do not reveal any corrosion, even though corrosion is actually present, should be low. Knowledge about how degradation occurs is also an advantage to be able to select the inspection points which will give the most valuable information.

Following the argumentation that inspections increase the knowledge, one should always inspect everything, and in that way remove all the uncertainty. This will be extremely costly and the ALARP principle is not being followed. Consequently, an important question arises: how much is it necessary to inspect to be sure that you do not inspect so much that it ends up in gross disproportion to the costs and benefits of doing inspections? In other words, the cost should be weighted against the value and need for new information (inspection results).

2.2 Inspection Management

Inspection planning is an important part of inspection management and today is based on Risk-Based Inspection, RBI analysis. Inspection management and risk management have a lot in common, as both of them strive to control unwanted events and consequences. Below are some points that can be used as guidelines when ensuring a good inspection management process:

- The inspection management should have an outstanding understanding of the system performance.
- The models that are used should be "sufficiently accurate" representations of the world; their goodness in describing the world has been evaluated (Aven, 2004).
- All observable quantities are precisely defined.
- The meaning of risk and uncertainty should be consistently treated and fully understood.

- The background information for the analysis is well documented and available to all parts: dose planning, performing and evaluating the inspection.

In Aven (2004), the above-mentioned points are used to highlight the factors necessary to ensure a high quality risk analysis. These points are not very different when it comes to inspection management and planning. Inspections are performed to reduce the uncertainties and mitigate risk related to a leak. A leak may have several different consequences, some of which may be very serious with the possibility of several fatalities; considering the Piper Alpha accident as an example, see Lord Cullen (1990). Inspection management and risk management are therefore related. Inspection management based on risk, known as Risk-Based Inspection, focuses the inspection on areas where the consequence of a leak is most severe, so it will be possible to act before a leak occurs. The following section will give a short description of the RBI analysis, and the different uncertainty factors. A description of an Extended RBI analysis, ERBI analysis, which includes the uncertainty factors, will be presented in Sections 2.2.2 and 2.2.3, see also the Appendix.

2.2.1 Risk Based Inspection, Hot Spots and Corrosion Groups

Risk based inspection, RBI, is a framework for determining where, what, how and when to inspect in a cost-effective manner, ensuring that safety requirements to personnel and environment are fulfilled. When doing inspections, it is normal to inspect locations where the condition being discussed is expected to be most severe DNV (2009). These locations are called hot spots. Hot spots with the same degradation mechanisms belong to the same corrosion group, meaning that the hot spots in this group are exposed to the same internal or external environment and made of the same material, thus having the same degradation mechanism. These groups should be organised so it is natural to relate inspection results in one part of the group to the hot spots in the remaining part of the group; see DNV (2009).

The RBI analysis is used to locate the areas exposed to the highest risk and in need of inspection. In the RBI analysis, different areas are divided into different consequence and probability categories, based on expected values. If the analysis concludes that the combination of probability of significant corrosion or erosion and the consequence of corrosion/erosion is unacceptable, it is decided that inspection is necessary.

Inspections may also be necessary if some conditions in the piping are unknown or insecure. In situations where the consequences of a leak are very high, inspections are done to look for surprises or to check assumptions which the RBI analysis is based on. Furthermore, when the RBI analysis recommends inspections, the next step is to decide how much to inspect. This will, as already mentioned, be the main focus of this thesis, and the number of inspections will depend on the acceptable level of uncertainty.

After an RBI analysis has been performed, a time to inspection will be recommended. The time is dependent on the probability and consequences of failure for the component/corrosion group/system, etc. being studied, but, according to Selvik, et al.

(2011), does "*fail to bring into account all the relevant uncertainties*". This means that all the relevant uncertainties in the RBI analysis are not revealed when only focusing on probabilities. Not all uncertainties can be expressed by probabilities; see Section 2.2.2.

In an RBI analysis, one is forced to produce probability estimates to be able to perform a risk estimate. When deciding these probabilities (P), different assumptions have to be made, and the probabilities that are used are based on the best available background knowledge (K). Often the background knowledge is weak, and the assumptions that are made are wrong. In some situations an assumption may be "constant sand content of two percent", this assumption is necessary to say something about the piping degradation.

A probability for degradation failure is calculated based on this, and the probability is used to estimate the risk and thereby the time to next inspection. When presenting the probability and time to next inspection, the assumption of two percent sand content is often forgotten. When introducing this assumption, an uncertainty factor follows. What if this assumption is wrong? Will it influence the time to next inspection (the decision), and how much can it change before the time to next inspection changes (sensitivity)?

The example of two percent sand content is far-fetched and in many situations this assumption is checked using sensitivity analysis. Nevertheless, there is a need for a more systematic approach to handle the different uncertainty factors. Not all uncertainty factors are as visible as the one mentioned above; some may be difficult to reveal, and experience may be necessary.

Let us take another example. Consider a case where you have a low probability of a leak, and the consequence of failure is classified as medium. Low probability of a leak is calculated based on degradation rate. This degradation rate is calculated based on an assumption: no presence of corrosive sources. The calculation of degradation and, following that, the probability of a leak is then conditioned on this very important assumption. If the only information that is being communicated to the management is that the probability of a leak is low, important information is hidden and the decision regarding time to next inspection may be influenced. If one assumes that no corrosive sources are present, one will normally not plan for inspection in the first couple of years. On the other hand, if corrosive sources are present an expected degradation will be calculated and inspection will be planned. If one expects fast degradation, time to next inspection will be short to make sure that maintenance is performed before a leak occurs. It follows that it is clear that this assumption is important, and should be communicated to the management.

This example is a bit far-fetched, but the point is that the background knowledge, often expressed by assumptions, may "hide" uncertainty, and these uncertainties are known as uncertainty factors; see Selvik and Aven (2011), and Selvik et al. (2011). They present a method for how to handle uncertainty factors. The basic concept of this method will be presented below.

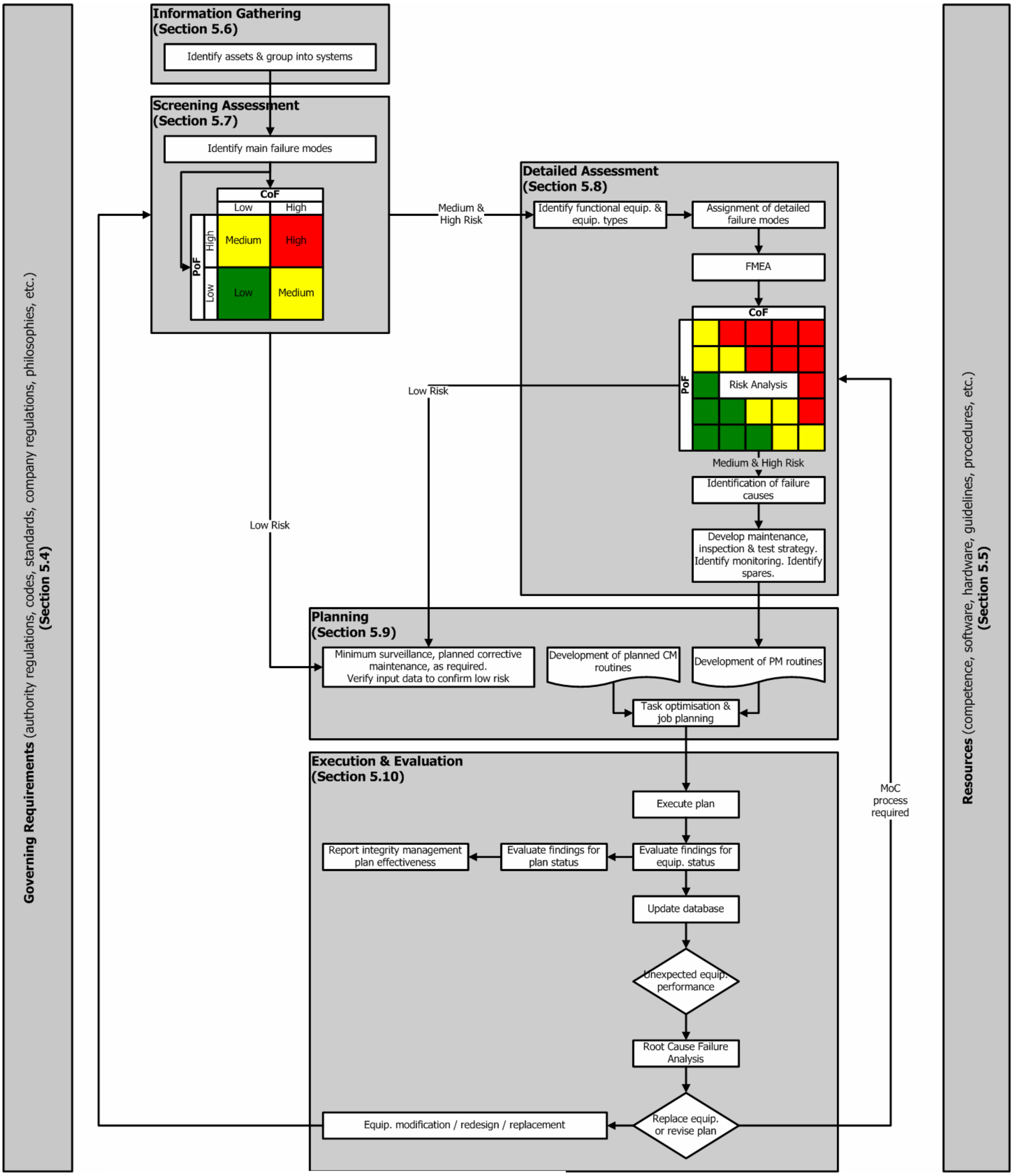

Figure 2.1 RBI process, DNV (2009).

2.2.2 Uncertainty Factors in the RBI Analysis

Motivated by the example in the section above, the need for an evaluation of uncertainty factors can be justified. In the method presented in Selvik et al. (2011), the assessment of uncertainty factors is added as an extra decision support after the traditional RBI analysis has been performed. They denote this as an extended RBI analysis: ERBI.

The ERBI analysis is also based on a different risk perspective than the RBI analysis presented in DNV RP-G101 (DNV, 2009). The ERBI analysis is in accordance with the risk perspective presented in Aven (2010). In this definition of risk, probability is being replaced with uncertainty, making probability a tool used to describe uncertainties, conditioned on the background knowledge. As a consequence, the focus changes from assessing probabilities and expected values to describing uncertainties. Since probabilities can not describe all uncertainties, an evaluation of the different uncertainty factors is required.

The ERBI analysis follows the same methodology as an RBI analysis, but with a broader perspective on risk, as mentioned above. Risk is then seen as a combination of the event (A), the consequence (C) and the uncertainties (U) about A and C; see Aven (2008). Probabilities, P, are used to describe the uncertainties related to the occurrence of A and its consequences C. P is based on the best available knowledge and will therefore not be able to describe the uncertainties “hidden” in the background knowledge.

The ERBI analysis includes a risk perspective which gives a broader risk picture, and includes uncertainties which may be hidden in the assumptions (which are based on the background knowledge). These “hidden” uncertainties are called uncertainty factors. Including an evaluation of uncertainty factors makes sure that the focus in the RBI analysis is on describing uncertainties and not just probabilities, and consequently on being able to reduce the occurrence of unwanted situations and surprises.

In addition to a broader risk perspective, the ERBI analysis presented by Selvik et al. (2011) presents a potential for methodological improvements, consisting of extended uncertainty assessments. The RBI methodology presented in DNV (2009) will still be the platform, but the ERBI analysis requires an extended incorporation of the uncertainty factors. Some may argue that uncertainty factors are already included in the RBI analysis, but a systematic methodology is lacking.

Studies like those of Geary (2002), Herzog and Jackson (2009) and Simpson (2007) indicate that uncertainties in assumptions made in the RBI analysis are limited, reflected in the final result. None of the above-mentioned articles includes an evaluation of uncertainty factors.

Before presenting the methodology for the ERBI analysis, I would like to refer to Vinnem (2008). He has performed a case study of an LNG plant located in Risavika, an urban area on the Norwegian west coast. He is attaching an assumption which was made when evaluating the risk attached to this plant. This assumption says that “in the event of impact of a passing vessel on an LNG tanker loading at the quay the gas release would be ignited immediately, presumably by sparks generated by the collision itself".

Vinnem not only disagrees with the assumption, but he also notes that a treatment of this assumption, such as a sensitivity study, is missing? This can be seen as motivation for why evaluations of the different uncertainty factors are needed. A change in this assumption in the LNG case could have influenced the decision regarding the location of the plant. At least the effects of this uncertainty factor should have been investigated, according to Vinnem (2008).

2.2.3 Methodology for Extended RBI Analysis

In this section, the ERBI methodology presented in Selvik et al. (2011) will be described. As discussed in Section 2.2.2, the method is based on the RBI analysis presented in DNV (2009), but includes a broader risk and uncertainty perspective. The ERBI analysis is also based on a knowledge-based approach to probability; see Section 2.1.2. Figure 2.2 presents the framework for the extended methodology as presented by Selvik et al. (2011). Steps 0-3 represent the standard RBI analysis, while steps 4-6 include the new steps included in the ERBI analysis.

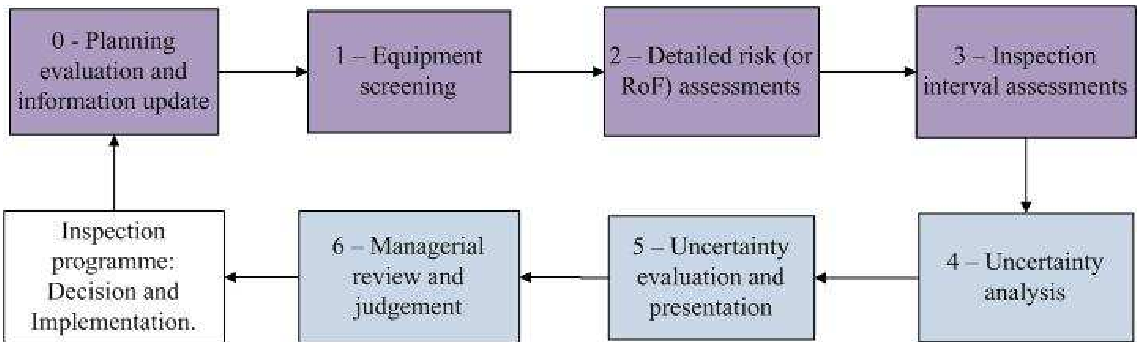

Figure 2.2 Framework for the extended RBI methodology, as presented in Selvik et al. (2011).

After performing an RBI analysis according to DNV (2009), Selvik et al. (2011) recommend an uncertainty analysis, which consists of:

- *Identification of uncertainty factors*
- *Assessment and categorisation of the uncertainty factors with respect to degree of uncertainty*
- *Assessment and categorization of the uncertainty factors with respect to sensitivity*
- *Summarization of the factors' importance*

It follows that the first step is to identify the uncertainty factors. These are factors which may come from assumptions made during the risk assessment. The next step is to rank the different uncertainty factors using a score: high, medium or low. This score is motivated by Flage and Aven (2009) and, in Selvik et al. (2011), is summarized as:

<u>High uncertainty</u>
If one or more of the following conditions are met:

- *The assumptions made represent strong simplifications*
- *Data are not available, or are unreliable*
- *There is lack of agreement/consensus among experts*
- *The phenomena involved are not well understood; degradation models are non-existent or known/believed to give poor predictions*

<u>Low uncertainty</u>
If *one or more of the following conditions are met:*

- *The assumptions made are seen as very reasonable*
- *Much reliable data are available*
- *There is broad agreement/consensus among experts.*
- *The phenomena involved are well understood; the degradation models used are known to give predictions with the required accuracy*

Medium uncertainty is defined for the factors where there is a combination of the conditions from low and high uncertainty. Consequently, some uncertainty factors end up with high uncertainty, but this does not necessarily mean that they will influence the risk level and thereby the time to inspection.

The third step in the methodology introduces a degree of sensitivity. As an example, take the assumption: no presence of Microbiological Induced Corrosion, MIC. This assumption introduces an uncertainty factor, which may have a low, medium or high degree of uncertainty. Let us say that the degree of uncertainty is medium, but if MIC actually is present, it will influence the final risk level and thereby the time to next inspection.

This uncertainty factor therefore has a high degree of sensitivity, as presence of MIC strongly influences the degradation rate. The combination of the sensitivity, how much the factor is able to change the risk picture (time to inspection), and the degree of uncertainty, are interesting in a decision-making context. See Table A and Selvik et al. (2011) for an example of how this can be presented. The combination of the degree of uncertainty and sensitivity leads to the classification of the uncertainty factors' degree of importance. Uncertainty factors with a high degree of importance should be prioritised when the risk picture is being communicated to the management.

Let us introduce an example. Consider an n-year-old platform that is ready for inspection. Some of the carbon steel piping is expecting corrosion. It is assumed that all piping in a corrosion group is exposed to the same temperature, pressure and internal medium.

In this situation, the piping is assumed to be a gas-water-hydrocarbon multiphase system which can give uniform CO_2 corrosion. According to DNV-RP-G101 (DNV, 2009), areas where it is expected that water is in constant contact with the carbon steel will be chosen as hot spots, as CO_2 corrosion is most likely to take place at these locations. In some cases these hot spots may be very good, meaning that they are easy to locate. Good hot spots make it possible to feel secure that if corrosion is present in the corrosion group, it would at least be present in the hot spots. To make this simple, let us present a list of some of the assumptions that will be present when planning time to inspection for this corrosion group:

1. Water is in constant contact with the carbon steel

2. Inspection results are representative for the whole corrosion group

3. The operational parameters are constant over time

4. No presence of MIC (microbiological induced corrosion)

All the assumptions listed above represent different uncertainty factors. When performing the RBI analysis, the time to next inspection is estimated based on these assumptions.

The assessed risk, and thereby time to inspection, will vary if these assumptions turn out to be wrong or imprecise. The degree of the changes in the risk picture may be different for each uncertainty factor. The uncertainty factor introduced by the assumption of no presence of MIC (microbiological induced corrosion), is characterised below as having a high degree of uncertainty. MIC may occur if bacteria (from seawater) are present. In this example, it is not expected, but it may occur if the sulphate removal package (SRP) does not work as intended. MIC has never been detected, as it is often not inspected for either, in this corrosion group, but there exists a possibility of MIC corrosion; it is just not the most likely scenario. After identifying the different uncertainty factors introduced by the assumptions, the different degrees of uncertainty can be determined. The different degrees of uncertainty are:

1. Low Water is in constant contact with the carbon steel
2. High Inspection results are representative for the whole corrosion group
3. Low The operational parameters are constant
4. High No presence of MIC, microbiological induced corrosion

Further, each of these assumptions can be given a degree of sensitivity:

1. High Water is in constant contact with the carbon steel
2. High Historical data are relevant
3. Medium The operational parameters are constant
4. High No presence of MIC, microbiological induced corrosion

The uncertainty factor identified in the assumption regarding no presence of MIC is said to have a high degree of sensitivity. This means that this uncertainty factor is able to change the decision regarding the time to next inspection. If MIC is present, the corrosion rate will be higher, and significant corrosion will most likely occur earlier.

After assessing the different degrees of uncertainty and sensitivity, this is combined into a degree of importance, as listed below. Uncertainty factors with a high or maybe also medium degree of importance should then be communicated to the management. As seen in this example, the uncertainty factor which emerged from the assumption of no presence of MIC should be communicated to the management.

In many situations the management would ask for more information, like what would happen if MIC was present. Uncertainty factors like this are also often being communicated today, but not systematically, and the possibility of overlooking uncertainty factors "hidden" in the assumptions is present. It is clear that uncertainty factors are very important and, if missed, unwanted situations may arise.

Using the method presented in Selvik et al. (2011), the degree of uncertainty and sensitivity can be combined into a degree of importance. In this example:

1. Medium — Water is in constant contact with the carbon steel
2. High — Historical data are relevant
3. Low - Medium — The operational parameters are constant
4. High — No presence of MIC, microbiological induced corrosion

When presenting the results from the ERBI analysis, the assumptions with a high degree of importance should be highlighted. This is, to some degree, included in the RBI practice today. However, one may benefit from a more systematic approach to uncertainty factors, as presented in Selvik et al. (2011). The ERBI process is more time-consuming, but is recommended to be performed when dealing with decision making under uncertainty.

After evaluating the uncertainty factor's importance, the ERBI analysis recommends an uncertainty evaluation and presentation. This may give valuable information to the management.

The next step in the framework for the extended RBI methodology presents the role of managerial review and judgement. This step ensures that the various assumptions and uncertainty factors are seen in a broader picture, giving weight to different concerns, limitations and boundaries. Management review and judgement also reflect the fact that decision making under uncertainty needs to balance different concerns, like risk, cost and, in some situations, also reputation.

In this thesis, the focus is on the uncertainties related to factors which influence the occurrence and location of a leak. The aim of inspections is to locate these areas before a leak occurs. Different methods for calculating corrosion rates have been developed, and the input in these methods is based on the piping material, medium, temperature, pressure, etc. These calculation models are based on earlier experience and research.

In some cases the degradation rates are either higher or lower than estimated. A central assumption when performing inspection planning is the dividing of corrosion groups. This assumption includes an uncertainty factor. What if some of the areas in this corrosion group are placed in the wrong corrosion group? This may happen, but experience and training may reduce this possibility. Still, it is important to address the uncertainty, especially in situations where the consequences of wrong corrosion group are high. Often inspection points/hot spots are chosen to reduce the effect of "wrong" corrosion group, meaning that areas with the highest consequences are preferred when performing inspections.

When planning the time to next inspection, different assumptions are made. Often the most conservative assumptions or expected values are used. This may lead to quite a conservative calculation of degradation rate, and situations where significant corrosion is expected but not revealed during inspection may occur.

Consequently, how much should then be inspected in order to feel secure that no corrosion is present? Is it not natural to believe that this should depend on the factors' degree of uncertainty? Section 3.2.2 presents the choice of prior distribution in a Bayesian analysis, and how this prior distribution can be used to reflect some of the uncertainty. Still, it is important to remember that the prior distribution only reflects the uncertainties regarding the fraction of hot spots with significant corrosion (the distribution parameter), based on the available background knowledge, and that evaluation of the uncertainty factors is necessary.

In Section 1.6 risk is described as the combination of the event A, the different consequences C, the uncertainties attached to both A and C, the probabilities P (knowledge-based) used to describe U, a sensitivity S to see how variation in different input conditions and assumptions changes the risk picture, and given the background knowledge K. An alternative to this may be to describe risk using (A,C,Q,K), where Q represents the uncertainty. Some of this uncertainty may be presented using probabilities, P, while the remaining uncertainty factors are presented when doing an evaluation of the different uncertainty factors, UF. It follows that:

Uncertainty (Q) = P (A|K) and UF

This section has presented an extended RBI methodology, based on the RBI framework, but with a stronger and more systematic focus on uncertainties. The ERBI analysis highlights uncertainties which may be "hidden" in the assumptions on which the analysis is based. This leads to a broader presentation of the risk, in which the management will have to evaluate the important uncertainty factors and give weight to different concerns like cost vs. benefit (reduced risk). Consequently, this will reduce the possibility of surprises and unwanted events. For a more comprehensive example regarding the treatment of uncertainty factors, the reader is referred to the Appendix.

2.3 Bayesian Updating

The Bayesian updating process is a well established method for the incorporation of new information. There are several books which describe Bayesian updating; this thesis will just touch the most basic parts of the theory. For more advanced theory, see Bernardo and Smith (2000), Ghosh et al. (2006) or Singpurwalla (2006). Bayesian updating is a strong tool for handling new data, where updating the probability of an event has the main focus. For Bayesians, probability is a measure of uncertainty based on the available background knowledge. This is different from the relative frequency approach to probability, where probability is the fraction of "successes" in the long run, as already explained in Section 2.1.2. To Bayesians, the relative frequency of an event is known as a chance. The probability of an event, P(A), can change as more data is revealed. It is this opportunity to learn from experience that is the known as Bayesian updating. The original belief before more data is available, P(A | H), is called the prior distribution and is based on (given) the best available background knowledge H. When this probability is updated it is called the posterior distribution, P(A| X, H), where X represents the new data (observable quantities). The posterior distribution represents the probability of event A occurring, given that data have been observed and the background knowledge H. Using Bayes' formula to compute the posterior distribution we get:

$$P(A|X) = c\, P(X|A)\, P(A)$$

where c is a normalizing constant which ensures that the sum (integral) over the density equals one. P(X | A) is the probability of X occurring given that A has occurred, also known as the chance distribution. H is removed from the equation, but it is important to remember that all these numbers are based on the background knowledge. Sensitivity analysis can be performed to see how changes in the input data (background knowledge) may change the output.

2.3.1 Bayesian Inference

Say that there exists a θ which is important for making a good decision. Let H, the background knowledge, denote all that is known about θ. More information about θ will become available; this new information can be found from the data $\mathbf{X} = X_1, \ldots\ldots X_n$, where X_i represents one observation/measurement. The prior distribution, $f(\theta \mid H)$, represents our initial knowledge, uncertainty, about θ. Using Bayes' formula we can calculate the posterior distribution:

$$f(\theta \mid \mathbf{X}, H) = c\, f(\mathbf{X} \mid \theta, H)\, f(\theta \mid H) \qquad \textbf{Equation 1}$$

As already mentioned, c is a normalizing constant such that the integral over the density equals one and $f(\mathbf{X} \mid \theta)$ is the likelihood function of θ given **X** . Equation 1 can therefore be written as:

$$f(\theta \mid \mathbf{X}, H) = c\, L(\theta \mid \mathbf{X})\, f(\theta \mid H) \qquad \textbf{Equation 2}$$

The objective of this updating process is to assess the uncertainty of θ.

Furthermore, it is often the future which is of interest. Starting with a prior distribution, updating to a posterior distribution, and further combining this and the law of total probability, finds the predictive distribution. The probability of a future event or sequence of events can be written as:

$$P(X=x) = \int_{\theta} P(X = x \mid \theta)\, F(d\theta) \qquad \textbf{Equation 3}$$

where x is the outcome of the event (or sequence) of interest, $F(\theta)$ is the distribution function of θ, prior distribution, and $P(X = x \mid \theta)$ is known as the chance distribution of X. For simplicity, the background information, H, is suppressed in the equation, but should not be forgotten.

Further, let **X** be a sequence of exchangeable variables that can take the value of 0 or 1, a Bernoulli sequence. θ is then the fraction of ones. The predictive distribution can then be written as:

$$P(X_1= 1,\ldots, X_k = 1 , X_{k+1} = 0,\ldots, X_n= 0) = \int_{\theta} \theta^k (1-\theta)^{n-k} F(d\theta), \qquad \textbf{Equation 4}$$

This is known as de Finetti's theorem for zero-one exchangeable sequences, meaning that if you have an exchangeable sequence of random variables, these variables can be handled as if they were independent, conditional on the parameter θ. Exchangeable means "a sequence of observations where the joint probability distribution of any finite subsequence of observations is invariant under the permutations of the order of observations," Aven (2010, p. 161).

$\theta^k (1-\theta)^{n-k}$ is known as the chance distribution and F is the prior distribution of θ, which shall represent the knowledge about θ before the new data is observed. The selection of prior distribution can vary and is explained further in the next section.

2.3.2 Conjugate Analysis and Prior Distributions

The choices of prior distribution are not easy, and much has been written regarding them; see for example Ghosh et al. (2006), Bernardo and Smith (2000) or Singpurwalla (2006). Different methods for selecting prior distributions can be used: the so-called non-informative distributions which intend to reflect total lack of knowledge. For a binomial case, the parameter θ (on the interval [0, 1]) will have a non-informative prior distribution if a uniform distribution is used; see Figure 3.7.

It can be claimed that there always exists some degree of knowledge about a phenomenon or the parameter for which the prior distribution is assigned. As Gudmund R. Iversen writes in his book about Bayesian Statistical Inference from 1984, "*...research is never done in a vacuum, and if nothing were known about a parameter we would not have thought of doing research in the first place.*" This is absolutely valid for the situation which is studied in this thesis. It would not be interesting to know the fraction of hot spots with significant corrosion if we did not know that corrosion existed and would cause a leak if not controlled or avoided.

At least it is known that the fraction exists and in theory can take all values between zero and one. In most cases we also know more, due to different degradation mechanisms, history and research. When this is reflected in the prior distribution, it is called an informative prior distribution. A non-informative prior distribution is also used in situations where all values of the parameter are considered to be equally likely; this means that "*an interval of values of fixed length is equally likely no matter where the interval is located within the relevant rage of the parameter*" Iversen (1984).

Informative prior distributions will be very informative in situations where some parameter values can be assigned a prior probability equal to zero. Doing this means that certain values of the parameter are absolutely impossible, and no matter what evidence (new research) shows, the posterior probability will always be zero. Due to this, care should be used when assigning a prior value equal to zero. So, as Lindley (1985, p. 104) writes "*leave a little probability for the moon being made of green cheese, it can be as small as 1 in a million, but have it there since otherwise an army of astronauts returning with samples of the said cheese will leave you unmoved.*" For a more comprehensive discussion regarding the use of prior distributions, see Bernardo and Smith (2000, pp. 357-370) or Ghosh et al. (2006).

When trying to find the prior distribution which best describes the available background knowledge, informative or not, it is useful to check whether a conjugate prior distribution exists. This distribution ensures that the prior and posterior distribution belong to the same class of distributions. Consequently, this will make the Bayesian updating easier, but a conjugate distribution should only be used in situations where it also accurately expresses the prior knowledge. The Beta (α, β) distribution is a conjugate distribution for the Bernoulli (n, θ) distribution, which are the distributions that will be used in this thesis. The Beta distribution is not only used because it is a convenient choice, but also because it reflects the prior knowledge about the fraction of significant corrosion in all the possible situations considered in this thesis.

2.3.3 Bernoulli and Beta Distribution

A Bernoulli distribution is a discrete distribution function, used in situations where the values are either 1, with a chance of success equal to θ, or 0 with chance 1- θ. The probability function can be expressed as:

$$0 < \theta < 1 \qquad\qquad x = 0, 1$$
$$Br(x \mid \theta) = \theta^x (1-\theta)^{1-x}$$ **Equation 5**

The Beta distribution is a continuous distribution where:

$\alpha > 0, \;\; \beta > 0 \qquad\qquad 0 < \theta < 1$

$$Be(\theta \mid \alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$$ **Equation 6**

$$E(\theta) = \frac{\alpha}{\alpha+\beta}$$ **Equation 7**

$$Var(\theta) = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$ **Equation 8**

Consider a case where you are interested in the probability of drawing a blue ball and in the example from Ghosh et al. (2006):

$$X_i = \begin{cases} 1 & \text{if the } i\text{th ball is blue;} \\ 0 & \text{otherwise.} \end{cases} \qquad i = 1,2,....,n$$

where n is the number of drawings and the X_i s are exchangeable. The X_i 's are then Bernoulli distributed, $Br(1,\theta)$,with a probability of a blue ball θ. Let the knowledge of θ be represented with a Beta prior distribution.

Due to Bayes' formula, the posterior density can be written as:

$$f(\theta \mid \mathbf{X} = \mathbf{x}) = C(\mathbf{x})\theta^{\alpha+r-1}(1-\theta)^{\beta+(n-r)-1}$$

Where $r = \sum_{i=1}^{n} x_i =$ number of blue balls and $C(\mathbf{x})^{-1}$ is the denominator in the Bayes formula.

Compared to Equation 5, it is clear that this is also a Beta distribution, with $Be(\theta \mid \alpha + r, \beta + (n-r))$. Consequently the posterior mean and variance are:

$$E(\theta \mid \mathbf{x}) = \frac{\alpha + r}{\alpha + \beta + n - r}$$

$$Var(\theta \mid \mathbf{x}) = \frac{(\alpha + r)(\beta + n - r)}{(\alpha + \beta + n)^2(\alpha + \beta + n + 1)}$$ **Equation 9**

We can then see that the posterior mean is a weighted average between the prior mean and the information from the drawings, and that when the number of drawings increases, the weight from the prior distribution decrease. This equation also shows that if the alpha and beta values are high, more data are necessary to "move" the prior mean value. Thus, if your prior knowledge is strong, this can be reflected by choosing high alpha and beta values. Figure 2.3 shows how the beta distribution changes when the alpha (α) and beta (β) increase. Figure 2.4 shows how the distribution changes after ten drawings (or other new data, like inspections).

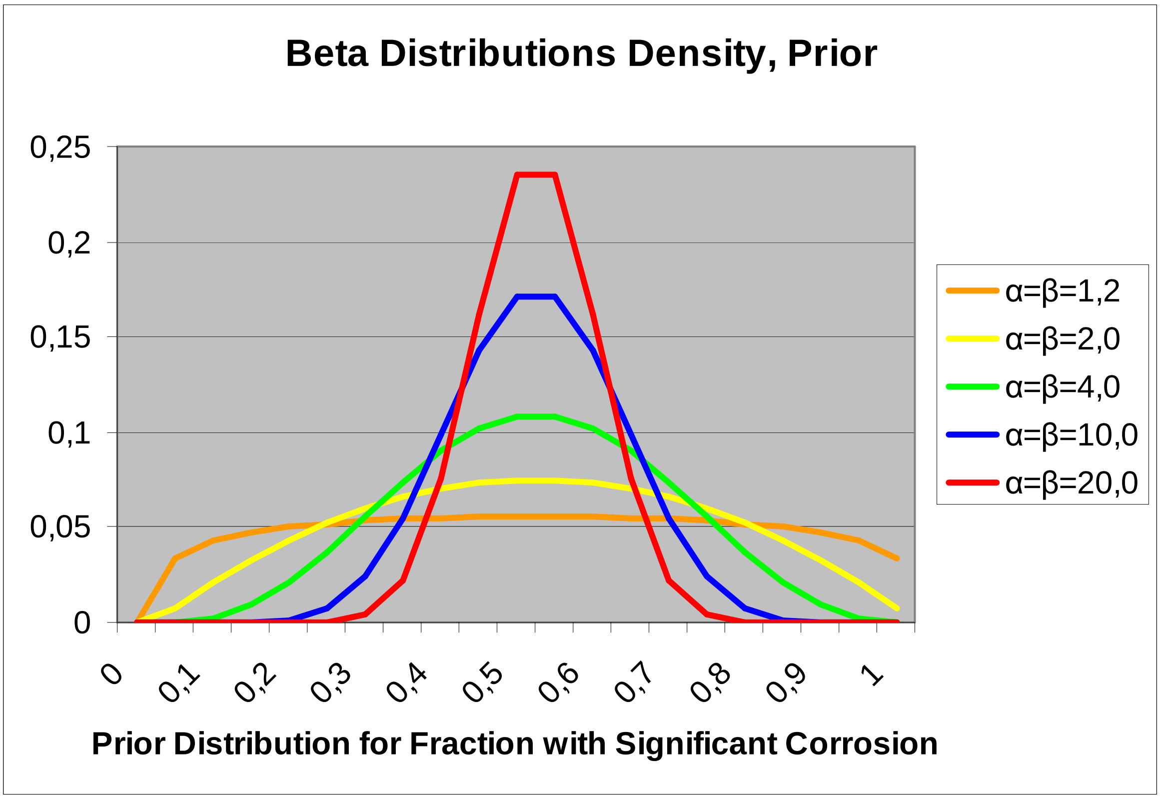

Figure 2.3 Different beta distributions, when $\alpha = \beta > 1$.

As already mentioned, Figures 2.3 and 2.4 demonstrate that the posterior distribution is much more sensitive towards new data when α and β values in the prior distribution are low. The density functions are moving towards zero after ten drawings without getting a blue ball, (or inspections without significant corrosion). For the prior distribution with the lowest α and β values, the posterior mean also becomes lowest after ten drawings without getting a blue ball.

Table 1 Table 1 presents approximate numbers of prior and posterior mean and variance for different values of α and β.

	α = β = 1.2	**α = β = 2.0**	**α = β = 4.0**	**α = β = 10.0**	**α = β = 20.0**
Prior, mean	0.5	0.5	0.5	0.5	0.5
Prior, variance	0.07	0.05	0.03	0.01	0.01
Number of new measurements	10	10	10	10	10
Posterior, mean	0.10	0.14	0.22	0.33	0.40
Posterior, variance	0.01	0.01	0.01	0.01	0.005

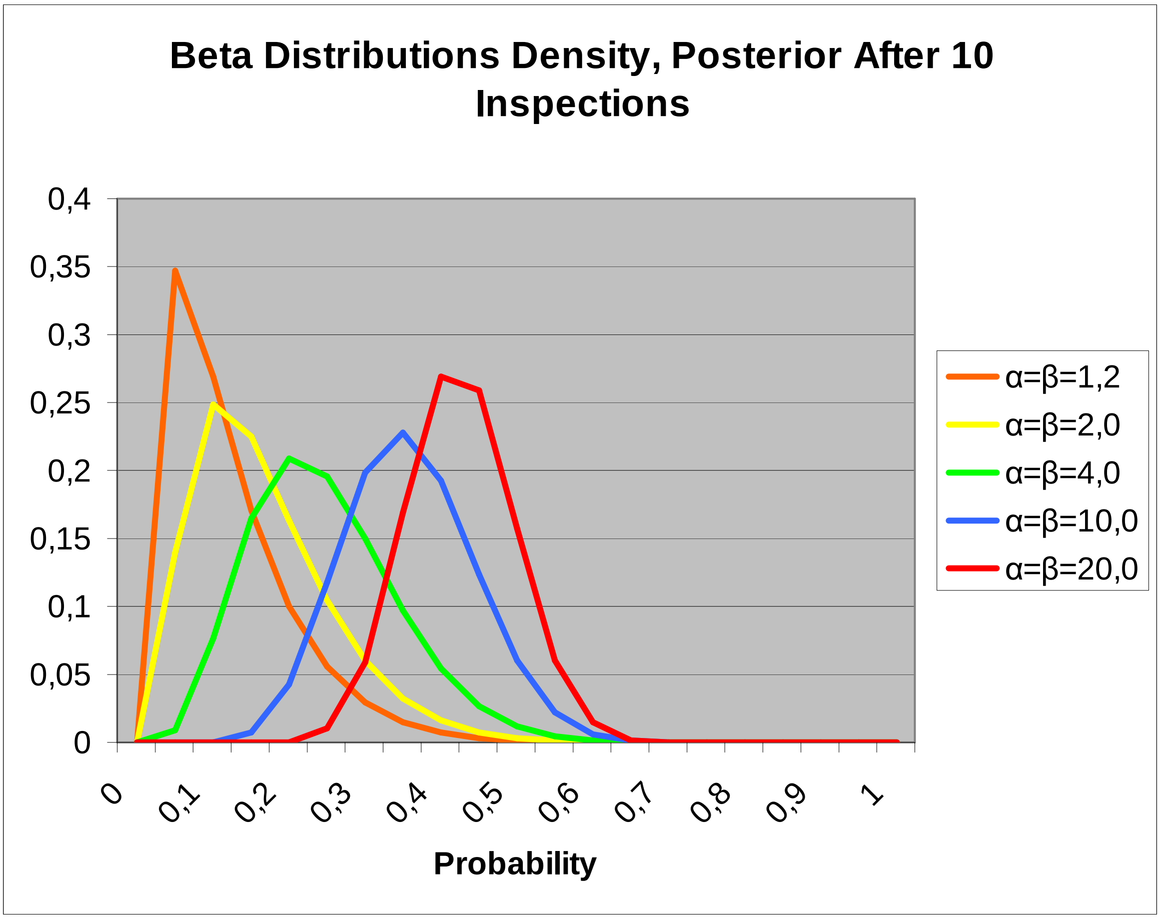

Figure 2.4 Posterior Beta distribution, after combination of prior distribution and new information (i.e. drawings, inspections…).

This chapter has introduced the background of the procedure developed in this thesis. The basic concepts of risk-based inspection, uncertainty factors, Bayesian updating and the beta and Bernoulli distributions have been presented. Chapter three will show how this theory can be used as decision support when planning inspections. More figures on how the beta distribution changes when more information becomes available will be presented in Section 3.1.

CHAPTER 3

DECISION SUPPORT FOR INSPECTION PLANNING

3.1 Application Example

Let us go back to the example presented in Section 2.2.3, where an n-year-old platform, ready for inspection, is considered. Some of the carbon steel piping is expecting corrosion. All piping that is exposed to the same temperature, pressure, internal medium, CO_2 content, etc. is put in one corrosion group. In this case the piping is a gas-water-hydrocarbon multiphase system which can give uniform CO_2 corrosion. According to DNV-RP-G101 (DNV, 2009), areas where it is expected that water is in constant contact with the carbon steel will be chosen as hot spots, as CO_2 corrosion is most likely to occur at these locations. In some situations these hot spots may be very representative, meaning that they are easy to locate.

Sometimes significant corrosion is expected in a corrosion group, but none of them reveal any corrosion during inspection. How much should then be inspected in order to feel confident that no significant corrosion is present in the corrosion group? During inspections there will not be time to perform calculations. This procedure does, therefore, give an output which can be used as decision support when deciding the number of inspected hot spots if none indicate significant corrosion. This is the method intended for situations where significant corrosion is expected but not found.

For situations where significant corrosion is not expected, the inspections will be carried out to verify the assumptions which indicate no significant corrosion, and to look for surprises. This may be in situations where the uncertainty factors are classified with a high degree of uncertainty; see Sections 2.2.2 and 2.2.3, see also the Appendix. Verifying assumptions may reduce the degree of uncertainty.

In situations where significant corrosion is not expected, the probability of significant corrosion is low and the method presented in this thesis will require a high number of inspections to “prove” that the probability of significant corrosion is even lower. The focus when inspecting and not expecting corrosion is not to reduce the probability, but to look for surprises or verify assumptions in order to check if the pressure, temperature, flow and so on actually are what were expected. Consequently, Bayesian updating will not be used before the output from the RBI (preferably an ERBI, see Section 2.2) analysis is ready. It is necessary to have a feeling regarding the state of the corrosion group and whether significant corrosion is expected before applying this method.

The method presented is based on the theory explained in Chapter 2 and will not be repeated. It is important to remember that this method will only be meaningful as long as the parameter θ (fraction of hot spots with significant corrosion) can be given a meaningful interpretation. It must be possible to define a large population (corrosion group) of similar hot spots. For cases where there are just a few hot spots in the corrosion group, other calculations/methods should be used to support the decision making, such as increasing the knowledge about the state of the corrosion group by inspecting a proportion of the total number of hot spots, and in that way reducing the risk to an acceptable level. The updating will not be required, as inspection of, for example, two out of four hot spots in a corrosion group will often reduce the risk to an acceptable level.

This chapter will present a method, based on Bayesian updating, that can be used as decision support when deciding the number of inspections. It will also be explained why this method is suitable in uncertain situations.

3.1.1 Updating Procedure

Let θ be the real chance of failure, the fraction of times when significant corrosion occurs in the hot spots. The value of θ is unknown, but information exists about what this value may be. Further, let X=1 if the inspection shows significant corrosion and X=0 otherwise. The sequence of zeroes and ones are exchangeable and Bernoulli distributed, with parameter θ. The uncertainty regarding the “true” value of θ, can be expressed by a beta (α, β) distribution. The choice of α and β values will reflect the knowledge about the true fraction of hot spots with significant corrosion. Background knowledge can, for example, be found from earlier inspection results, personal experience, DNV-RP-G101 (DNV, 2009) and more.

Figure 3.1.1 presents the basic concept of Bayesian updating, which is the theory behind the method introduced in this thesis.

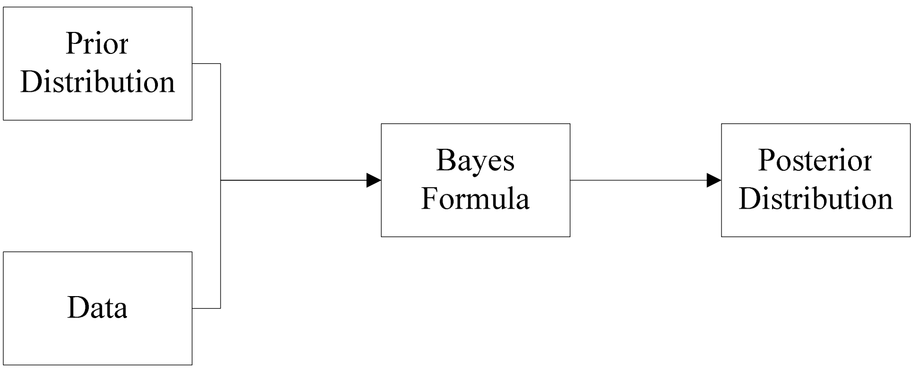

Figure 3.1 Bayesian Updating.

In this method, the data represents the inspection results and can be denoted by $(X_1, X_2,\ldots..,X_n)= \mathbf{x}$; the prior distribution represents the initial knowledge about θ and is described with a beta (θ, α, β) distribution. When assuming that **x** is exchangeable and Bernoulli distributed, Bayes’ theorem can be used to find the posterior distribution. The mean value in the posterior distribution can then be expressed as:

$$E(\theta \mid \mathbf{x}) = \frac{\alpha + r}{\alpha + \beta + n - r}$$ **Equation 10**

where α and β are parameters in the beta distribution, **x** is the sequence of hot spots, *n* is the number of inspected hot spots and *r* is the number of inspections with significant corrosion. In this situation, *r* is equal to zero as the method will only be used in situations where no significant corrosion is present.

Further, decide the number of inspected hot spots necessary to reduce the probability to an acceptable level. In other words, how much data is required to change your initial probability of significant corrosion given your background knowledge?. Inspections will increase the knowledge about the conditions in the corrosion group and may therefore also reduce some of the different uncertainty factors. The requirements with regard to the probability, indicating the degree of uncertainty related to the fraction of hot spots with significant corrosion, will of course always depend on the consequences of significant corrosion. The number of inspected hot spots when there are no hot spots with significant corrosion ($r = 0$) can be calculated:

$$n = \frac{\alpha}{E(\theta \mid \mathbf{x})} - \alpha - \beta$$

The posterior distribution is found easily as the beta distribution is a conjugate distribution for a Bernoulli distribution. The posterior distribution can therefore be expressed as a beta distribution with parameters α and $\beta + n$, when the number of inspected hot spots with significant corrosion equals zero ($r = 0$). See Section 2.3.3 for more explanation.

To end up with a number of hot spots, one will have to decide a value for $E(\theta \mid \mathbf{x})$. This expresses the mean value of θ in the posterior distribution after inspection, conditioned on the background knowledge. The requirement for the posterior distribution may vary as the quality of the hot spots may be different. This shows how the method has to be used in combination with other available knowledge; different situations will require different values of $E(\theta \mid \mathbf{x})$ and $Var(\theta \mid \mathbf{x})$.

Decision problems often consist of different uncertain aspects, and the probability of significant corrosion is just one of them. It is also recommended that the consequences of a leak and the “quality” of the hot spots are included. The different uncertainty factors, which may be hidden in the background knowledge, should also not be forgotten; see Chapter 2.2.

Further, in some situations hot spots are easy to locate and one can feel confident that they are representing the areas which are most likely to experience significant corrosion. The fraction of significant corrosion will often be lower for the whole corrosion group compared to the fraction of significant corrosion in the hot spots, at least if the hot spots are of "high quality". How should one account for this? Listed below are factors which could influence the value of $E(\theta\,|\,\mathbf{x})$:

- Consequence of significant corrosion
- The "quality" of the hot spots:
  - Easy to find?
  - Do these hot spots represent "worst-case" areas in the corrosion group?

It is not easy to find a solution to the choice of $E(\theta\,|\,\mathbf{x})$, but it is important to explain why one ends up on a certain value of $E(\theta\,|\,\mathbf{x})$. A sensitivity analysis can also be used to see how changes in $E(\theta\,|\,\mathbf{x})$ may influence the number of inspected hot spots. A value of $E(\theta\,|\,\mathbf{x})$ should not be used without explaining why.

For simplicity, the consequences are defined as high, medium and low. Areas where the consequences are defined as low are often not inspected and will "run to failure"; this method will not be needed and should therefore rarely be used in such situations. For situations where the consequences are high or medium, the tolerance for uncertainty is much lower and the choice of $E(\theta\,|\,\mathbf{x})$ should reflect this. I am suggesting that the output from this method is a sensitivity diagram; see Figure 3.2, which shows how the numbers of inspected hot spots influence the degree of uncertainty. When finally deciding the number of inspection points, this diagram can be used as support, and the reason for inspecting n hot spots can be explained with cost-benefit, "quality" of hot spots, consequences of significant corrosion and background knowledge. If the uncertainty factors, identified in the ERBI analysis (see Section 2.2), are classified with a high degree of uncertainty, a sensitivity analysis can be performed to check whether changes in assumptions will influence the number of inspected hot spots. If so, it should be communicated to the management, and they should decide if there is a need for more inspections.

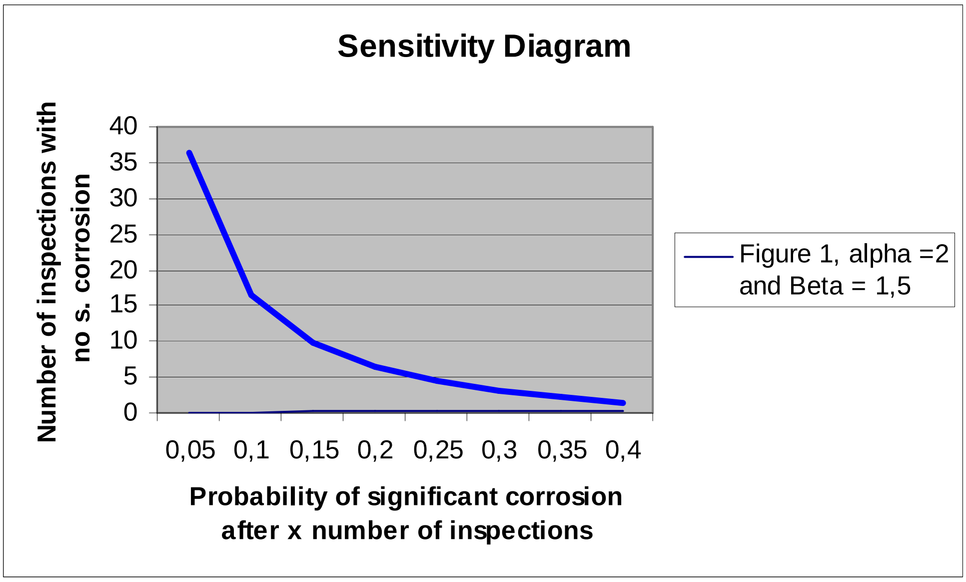

Figure 3.2 Sensitivity diagram, expected posterior value vs. number of inspections without significant corrosion.

Figure 3.2 shows how much $E(\theta \mid \mathbf{x})$ changes when inspecting more. This figure shows that the costs of reducing the probability from 0.10 to 0.05 require many more inspections than a reduction from 0.15 to 0.10. This can, for example, be used to say that ten inspections are enough as more inspections have little influence on the probability while the costs may increase significantly. For situations where the consequences are medium and the hot spots are good, (low degree of uncertainty related to the assumption of representative hot spots), maybe a $E(\theta \mid \mathbf{x})$ of 0.25 means that approximately five hot spots will then be inspected.

3.1.2 Selection of Prior Distribution

Selection of prior distribution is known as one of the challenges when using Bayesian updating, and the choice of prior distribution which best describes the background knowledge can be difficult. In the method presented here, the beta distribution has been selected as prior distribution as it simplifies the calculations and gives a suitable description of the possible values of θ in different situations. To make this method more user-friendly, some prior distributions will be suggested for different scenarios. These prior distributions are meant as examples and are all based on a beta distribution. The only difference will be the choice of α and β values. I will differentiate between five different scenarios:

1. Situations where the fraction of significant corrosion is either very high or very low.
2. Situations where the expected fraction is high, but can take all values between 0 and 1.
3. Situations where the expected fraction is symmetrically distributed around 0.5.
4. A uniform prior, where all values of θ are equally likely.
5. Situations where the expected fraction is low, but can take all values between 0 and 1.

For situation 1, the prior distribution will be U-shaped, meaning that both $\alpha = \beta < 0$. Figure 3.3 shows how different values of $\alpha = \beta < 0$ change the shape of the prior distribution, and how $\alpha > \beta$ and $\alpha < \beta$ both less than zero will influence the prior distribution.

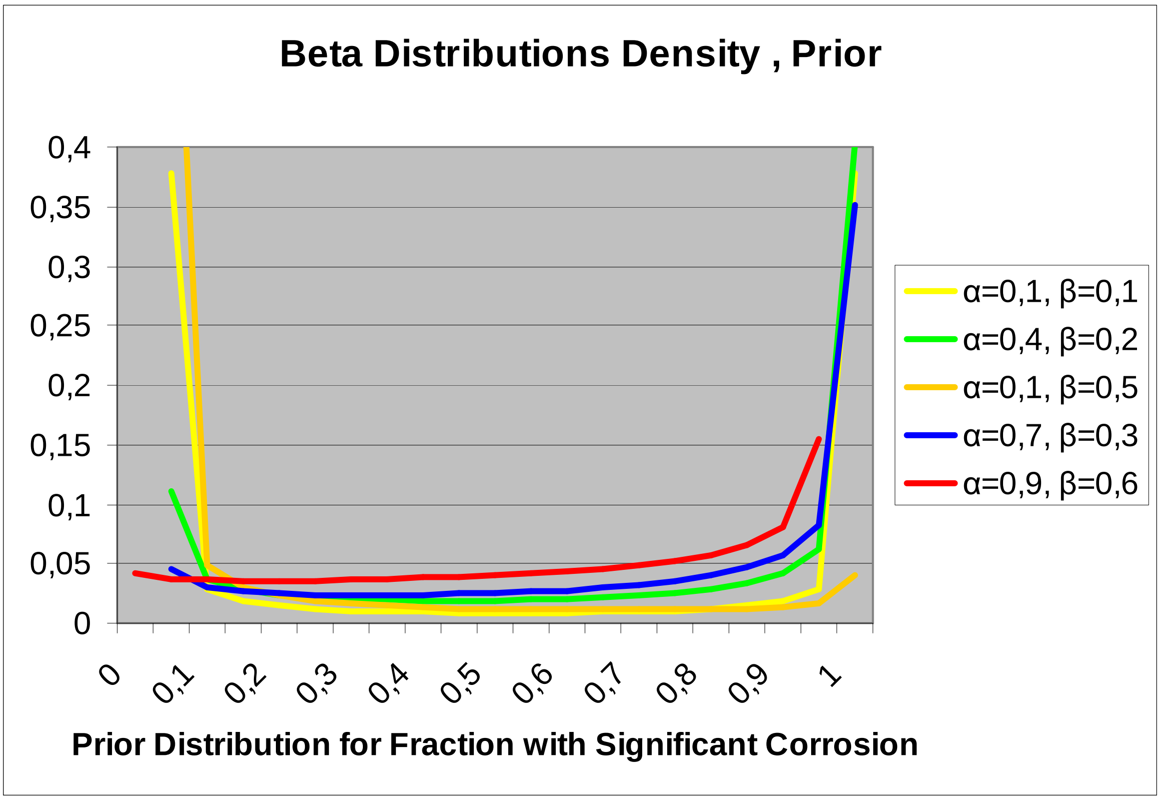

Figure 3.3 Different Beta Distributions when α = β < 0, situation 1.

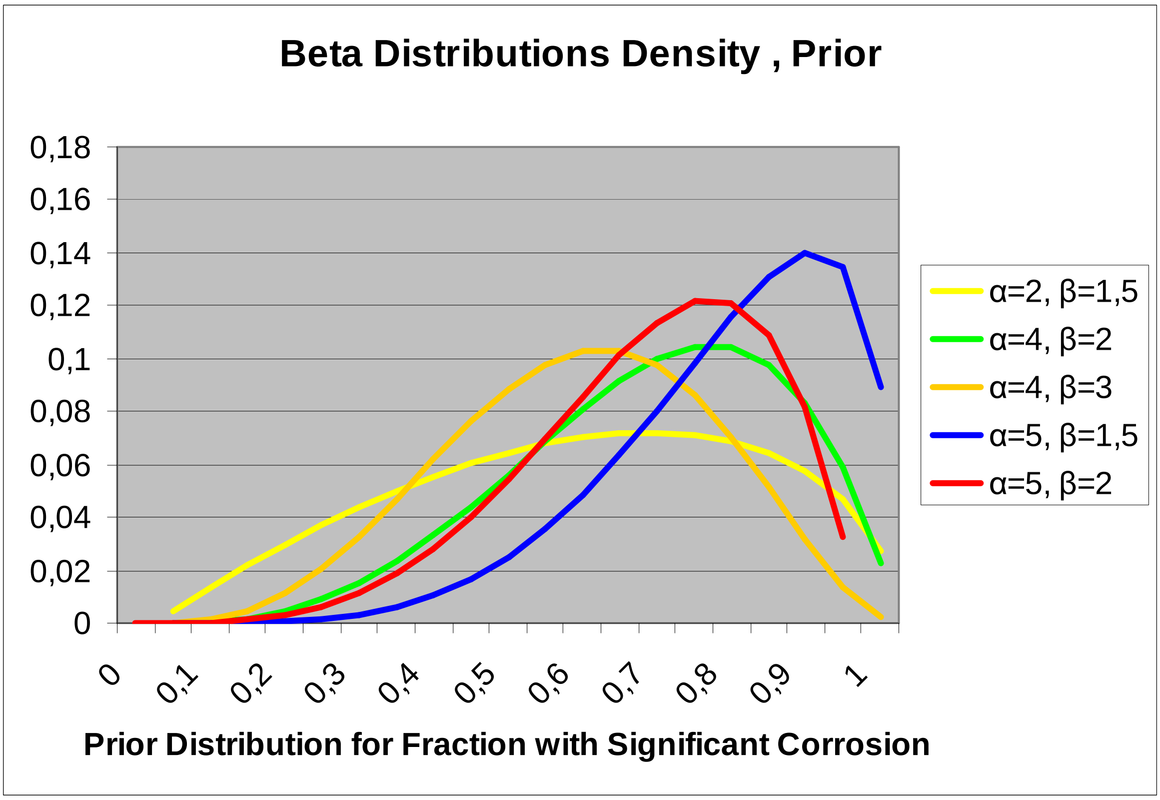

Figure 3.4 Different Beta Distributions when α > β > 1, situation 2. High expected fraction of significant corrosion.

For situation two, where the fraction of significant corrosion is expected to be high, the distribution may look as the ones in Figure 3.4. Here the main density of the prior distribution is located above 0.5. When choosing this distribution shape, one is expecting to find corrosion. A prior distribution like this will have $\alpha > \beta > 1$.

If the background knowledge is weak, a distribution, as shown by the yellow line in Figure 3.4, could be used. This may reflect situations where uncertainty factors with a high degree of uncertainty exist. Still, it is important to remember that even though the prior distribution can reflect some uncertainties, it will not reflect all. Important uncertainty factors may often be able to change the whole shape of the prior distribution.

An example may be that it is assumed that MIC is not present. The prior distribution is then selected based on this assumption; the prior distribution will not reflect the uncertainty factor related to the presence of MIC (and the other assumptions which represent the background knowledge). It will only reflect the uncertainty related to the frequency of significant corrosion, given no MIC. See Section 2.2.3 and the Appendix for a description of how uncertainty factors can be treated. Still, the prior distribution may reflect uncertainty factors related to the relevance and availability of historical data. Strong and relevant historical data may be reflected by choosing high alpha and beta values.

For situation five, $\beta > \alpha > 1$, and the expected fraction of significant corrosion is based on the background knowledge expected to be less than 0.5; see Figure 3. 5.

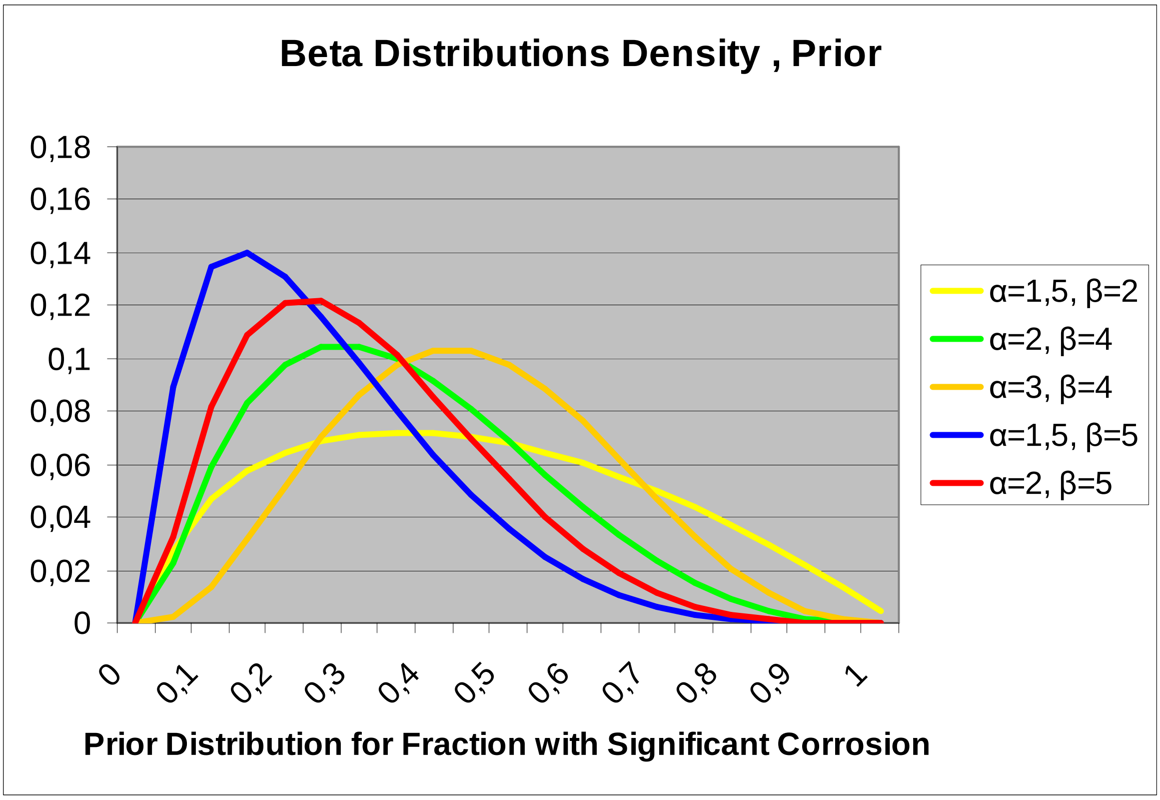

Figure 3.5 Different Beta Distributions when $\beta > \alpha > 1$, situation 5.

The values of α and β will be hold low as this allows the greatest influence from the data. An increase in α and β values will, in practice, say that we feel secure regarding the true frequency of significant corrosion, and more data are required to prove us wrong. Figure 3.6 shows how the prior distribution changes when α and β increase for a situation where the distribution is symmetrically around 0.5.

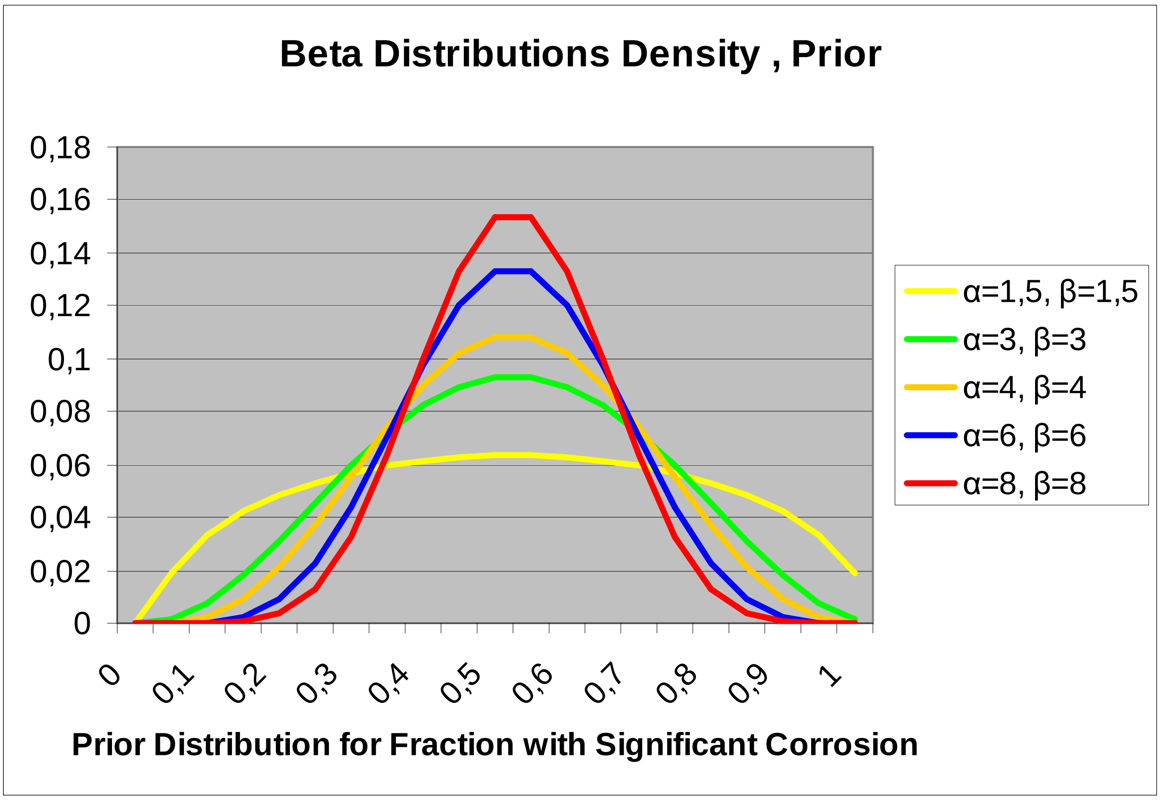

Figure 3.6 Different Beta Distributions when β > α > 1, situation 3.

For situation four, there is no information which indicates which value of θ is most likely to occur. This is a situation which is expected to be rare, as some sort of information almost always exists which will say something about the value of θ, the fraction of significant corrosion. See Figure 3.7.

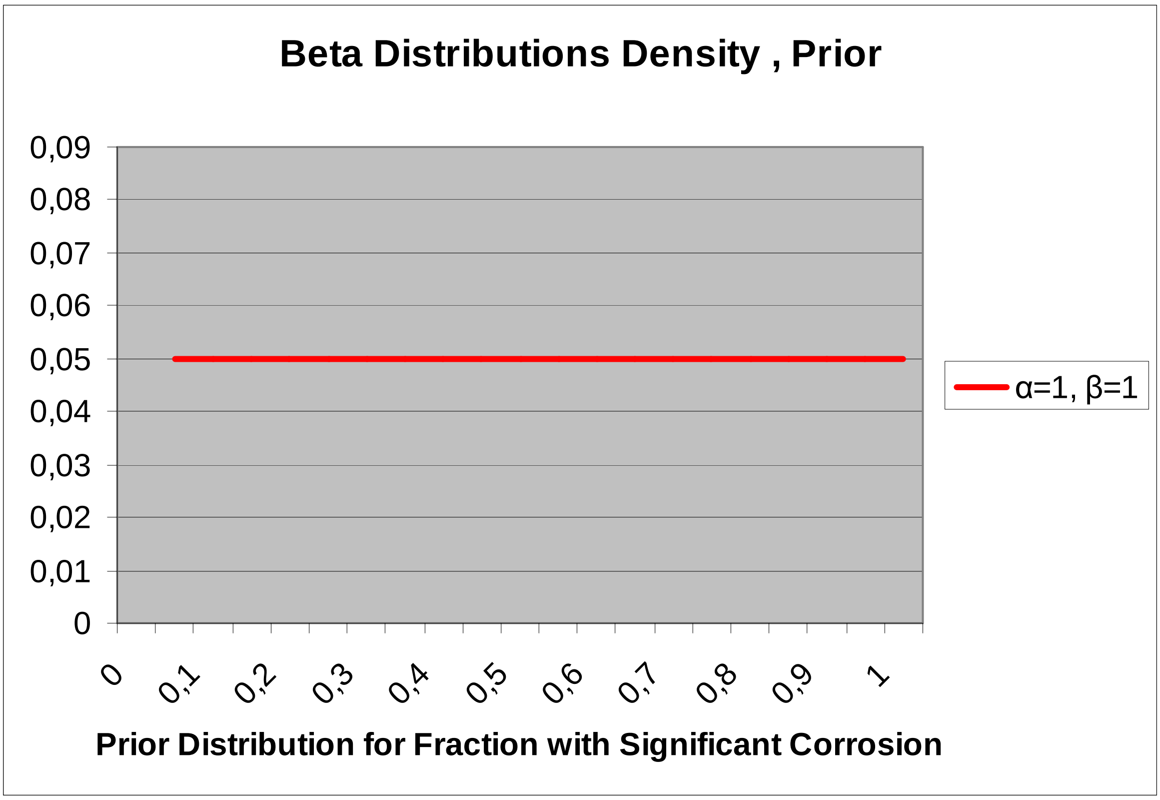

Figure 3.7 Beta Distributions when $\alpha = \beta = 1$, situation 4. Uniform distribution, there is no information about θ.

In the following section, a flow chart will be used to explain how the Bayesian updating can be utilised as decision support in the decision process when planning for inspection. For simplicity, the decision maker will be given five beta prior distributions to choose between. These distributions are chosen as they represent different corrosion scenarios, and small shape changes in the distribution will not result in huge changes in the number of inspected hot spots.

For decision makers familiar with the beta distribution, it is possible to assign their own prior distribution. To make this method easy to use and available for decision makers without knowledge of how to change the shapes of the distribution, five different distributions will be suggested. These five different distributions are based on the shapes described in the section above and presented in Figure 3.8.

To summarize this section, the beta prior distribution can take a lot of different shapes, and one of them will be suitable when describing the fraction of significant corrosion conditioned on the background knowledge for significant corrosion in a specified corrosion group. The next section will introduce the posterior distribution and how this changes when the number of inspection points increases.

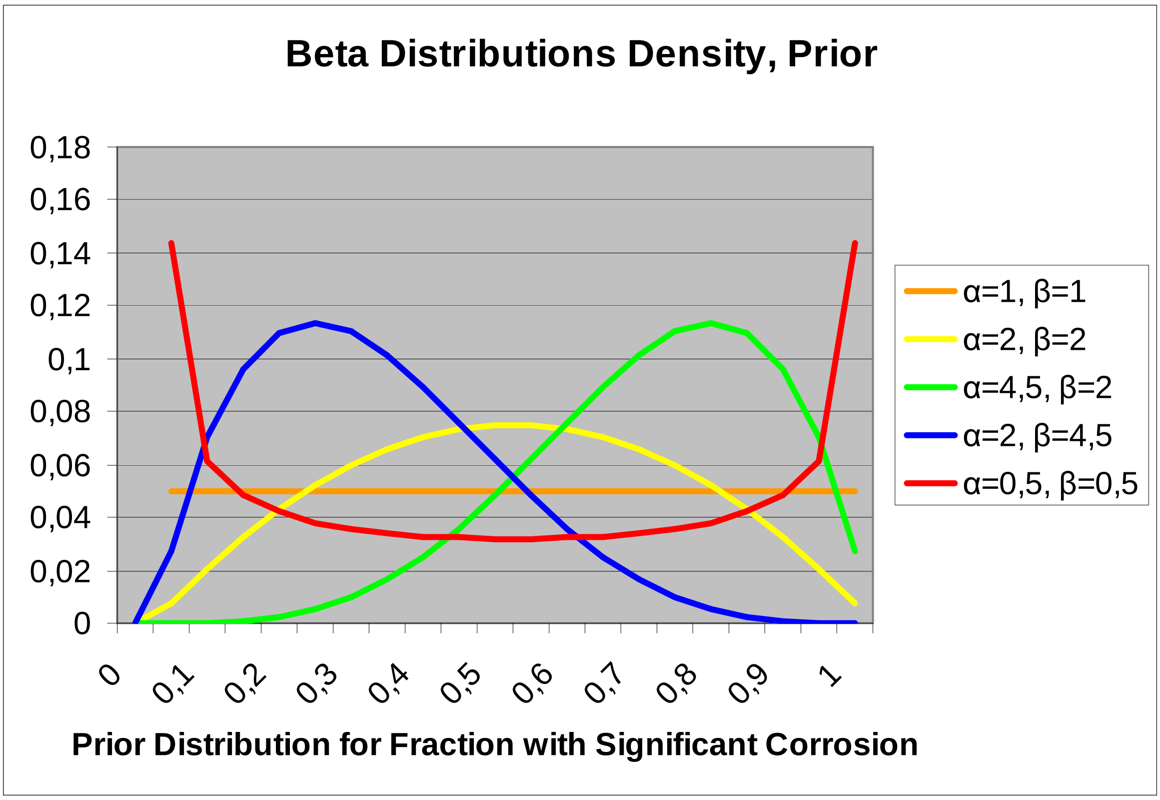

Figure 3.8 Beta Distributions for different values of α and β, representing situations 1-5 for different corrosion scenarios.

3.2 Practical Use in Decision Process

First, let us return to the introduction in this chapter. There is a situation in which it is expected that the corrosion group will have significant CO_2 corrosion. The outcome from the ERBI analysis says that this corrosion group must be inspected as degradation could have reached its limit; see DNV-RP-G101 (DNV, 2009) for more information. There are high quality (representative and easily located) hot spots available, and it is expected that the hot spots will have a high relative frequency of significant corrosion. The background information therefore indicates that a prior distribution with shapes like the ones presented in Figure 3.4 is a suitable choice, using the beta distribution with α = 4.5 and β = 2 which is also presented in Figure 3.8.

Following the flow chart presented in Figure 3.11, significant corrosion is expected and can be explained with the assumptions used in the ERBI analysis. The age of the system, the nominal wall thickness, the fact that it is a water-gas hydrocarbon multiphase system and so on can be used when explaining why significant corrosion is expected. Reasons like this can be found in DNV-RP-G101 (DNV, 2009). The choice of prior distribution has already been discussed, and the next step is now to look at the diagram which shows how the probability of significant corrosion is changing as the number of inspection points increases. This can be seen in Figure 3.9, situation 2.

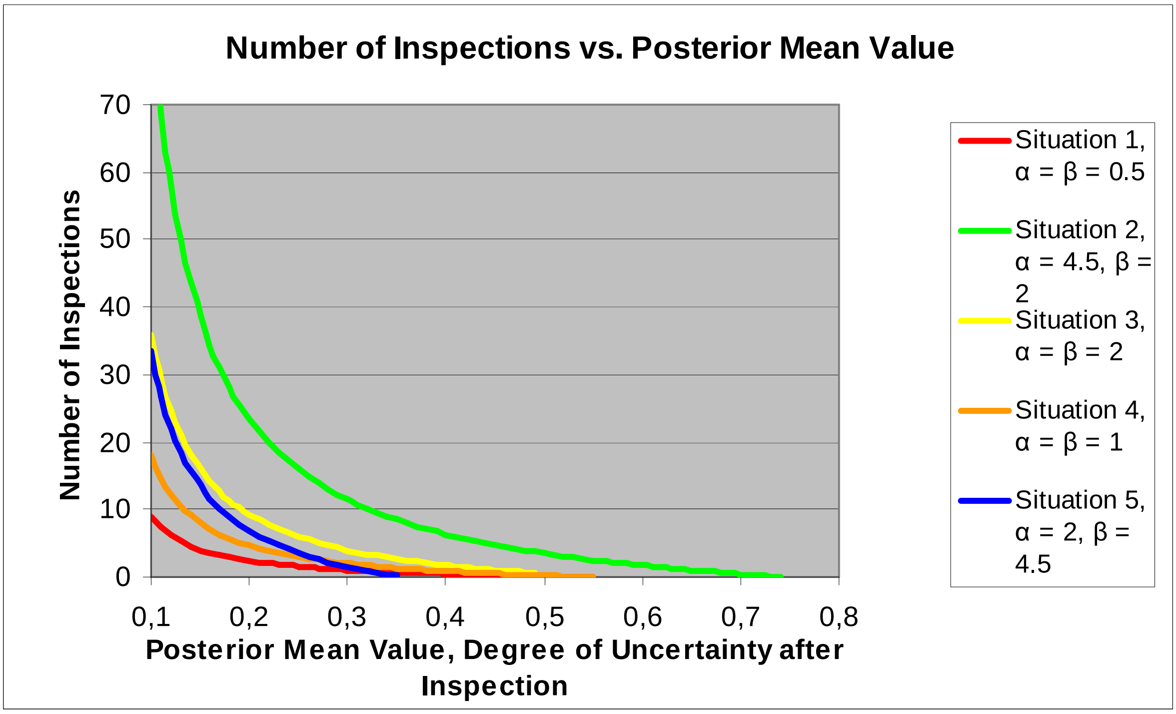

Figure 3.9 Sensitivity diagram, showing how the updated probability changes when the number of inspections changes for different situations.

For this corrosion group, it is considered that the hot spots are easy to locate and that if corrosion is present it will be found in the chosen hot spots, located where one expects that water is in contact with the metal. A posterior probability of significant corrosion in the hot spots equal to approximately 0.3, is considered satisfactory.

Consequently, nine hot spots are being inspected. After their inspection, one of them reveals significant corrosion. When taking a second look at this hot spot, it is clear that water from a valve has been dripping directly onto the hot spot. It follows that this hot spot is different; it is removed from the rest of the corrosion group and considered a special case. Another hot spot is then inspected. The new hot spot does not show any corrosion, and the uncertainty regarding the presence of significant corrosion is reduced to an acceptable level. In other words, I am convinced that no significant corrosion is present in the corrosion group.

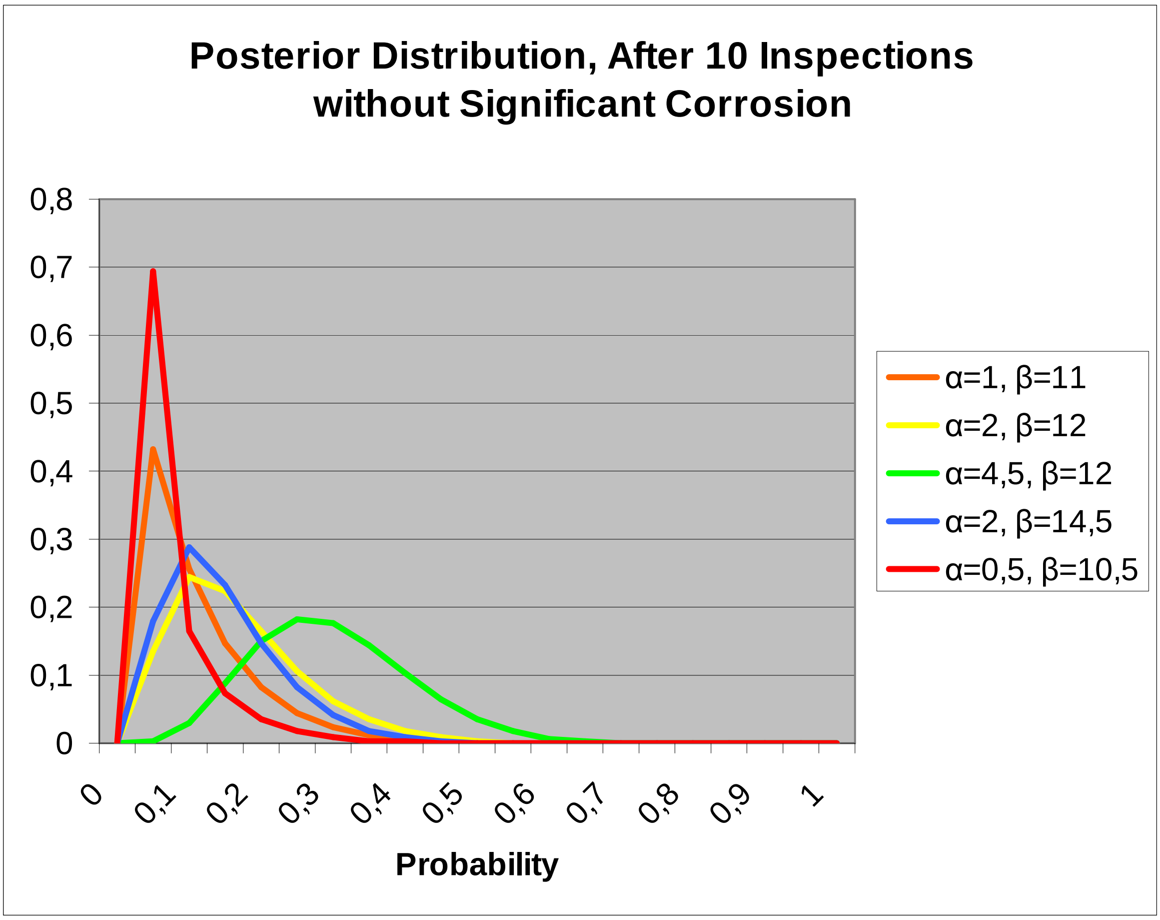

Figure 3.10 Posterior distribution for situations 1 to 5 after 10 inspections without significant corrosion. Alpha (α) and Beta (β) values updated using Bayesian updating.

When following the flow chart in Figure 3.11, it is important to explain each step, and why a certain prior distribution is selected. This will make it easier for others to trace the decision process and learn from good decisions. It can also be used to check the assumptions and find out what went wrong if a leak occurs after inspections.

If inspections do not reveal any expected significant corrosion, actions should be taken to find the reason. This will improve the knowledge about degradation mechanisms and is an important task after inspections have been performed. The Bayesian updating process will allow others to see how an expert has evaluated and weighted different information and concerns.

In addition, the process will be transparent and it will be possible for other experts, who may disagree with the final result, to reproduce the process and the assumptions that have been made. It is easier to discuss different assumptions and see how changes in the assumptions may influence the result, than to discuss a number.

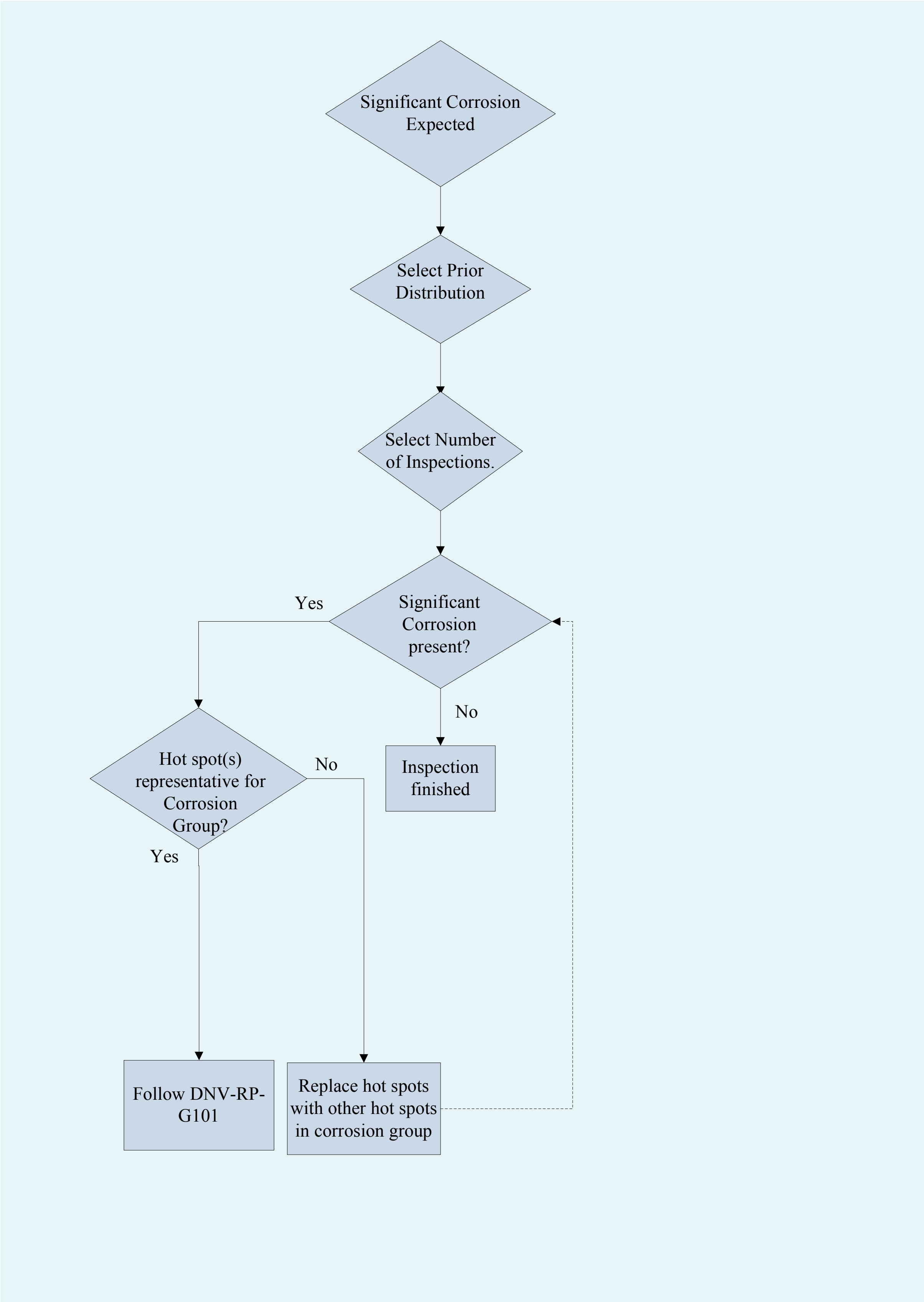

Figure 3.11 Flow chart which can be used as guidance when deciding the number of hot spots to be inspected in a large corrosion group.

3.3 Strengths of Bayesian Updating

The method presented above, based on Bayesian updating, provides a strong tool for decision making and will be useful in situations where significant corrosion is expected but not found. Bayesian updating in general can, of course, be used in many other situations, and this is just an example. See for example Aven and Eidesen (2007).

The main advantage of this method is the combination of background knowledge and new data, an approach which secures a systematic incorporation and treatment of new data and at the same time includes the background knowledge. Consequently, this combination makes it possible to use all the experience and background knowledge that exist and at the same time allow new data to convince us that the original belief was wrong or validate what was expected.

The focus on assumptions and why different actions have been made is also one of the strengths of Bayesian updating. All assumptions and reasons for different choices have to be addressed. In the method presented above, this is very clear when the reason for choice of prior distribution has to be explained. Why is this distribution chosen as a representation for the prior knowledge in that situation? Just the focus on this choice forces one to evaluate and comment on the background knowledge. Why (for example) believe that the presence of MIC will lead to a high probability of significant corrosion?

Furthermore, this will make it possible for someone without experience to look into earlier inspection plans and reports and see how experts have evaluated different concerns and assumptions. This may be used as training or to explain different decisions. It is not only novices who may benefit from this, it will also make the decisions traceable. The evaluation of different assumptions in combination with an evaluation of the uncertainty factors will prevent important assumptions from being hidden.

Moreover, it will be possible to trace a “bad” decision and figure out what and why the decision turned out to give unwanted or surprising consequences. If significant corrosion is present, but not found, it should be standard procedure to try and explain why. Are the models used to predict the degradation too conservative, or are other aspects also influencing the lack of corrosion?

In addition to classical statistics, Bayesian statistics addresses what is actually uncertain and not a number based on what has already happened. This is an advantage as it focuses on the future. We already know what has happened, but we do not know what will happen in the future. The already observed data may no longer be representative for the future, and Bayesian updating makes it possible to account for this. If something is known about the past, it is not necessarily certain that the behaviour will be the same in the future.

The next step will then be to look at what is known about the past and what is known about the future and then try to combine it into a reasonable estimate, expressed by the prior distribution. This is exactly what can be done when assessing the prior distribution: keeping what is relevant from the past and combining it with the future, making a prior distribution which reflects the belief and uncertainty regarding the event (situation).

Bayesian updating is therefore suitable when performing decision making under uncertainty. Still, it should not be used without an evaluation of the different uncertainty factors. When communicating the number of inspection points, an evaluation of the uncertainty factors should also be addressed. When uncertainty factors with a high degree of uncertainty exist, it may be useful to do the Bayesian updating using different prior distribution, checking the sensitivity of the uncertainty factor. If changes in an assumption result in a very different prior distribution, and following a very different number of inspection points, it may be classified as an important uncertainty factor, and should be communicated to the management; see Section 2.2.

Beside the other advantages of Bayesian updating mentioned above, it is easy, it does not require any difficult calculations and it is not time-consuming. That is why this could be used, without difficulty, as decision support when doing inspection management.

3.4 Challenges with Bayesian Updating

Bayesian updating is a well established method, and the use of this updating process has increased in the last couple of years. The formulas used in this thesis are quite simple; the combination of the Bernoulli distribution and the conjugate beta distribution has made the calculations easy. In other situations where these distributions are not suitable, the calculations may become more difficult, and computers that are able to handle complicated calculations are necessary. These complicated calculations have often been considered as one of the main disadvantages of Bayesian updating; see Bernardo and Smith (2000).

The next challenge when using Bayesian updating is the difficulty when deciding the prior distribution. How do you find a distribution which reflects your knowledge and which is reasonable? This may sometimes be a challenge, but in the method presented above the choice of prior distribution is clear.

It is also important to be aware of the limitations when using probabilities to describe uncertainties. As mentioned earlier, the choice of prior distribution is based on a set of assumptions; the uncertainty factors addressed in these assumptions are not visible if not evaluated after performing the standard RBI analysis. Some of these uncertainty factors may be revealed when explaining the choice of prior distribution. After identifying these uncertainty factors, they should be evaluated as presented in Section 2.2.

In situations where it is difficult to define the prior distribution, sensitivity analysis can be used. A sensitivity study can be used to check whether different choices of prior distributions will lead to another conclusion. Different prior distribution may come from different weighting of the background knowledge, trying to see how variation in the different assumptions and inputs changes the output.

Another question which may arise is the need for this method. As already mentioned, it is no use in introducing θ, if it can not be given a meaningful interpretation. This means that θ, interpreted as the long run frequency of exchangeable 0 and 1s, should exist. There is a need for a large number of hot spots in the corrosion group, in order to use the method presented above. Not all corrosion groups consist of a large number of hot spots, and the standard Bayesian approach, like the one presented here, should not be used. There is no need for a method like this as long as there are only a few hot spots in the corrosion group.

What happens in situations where the corrosion group contains a small number of hot spots? The important assumption of a large number of hot spots will not hold. What can be done if the Bayesian updating method leads to a number of inspected hot spots which is above the number of available hot spot in that corrosion group? It should not be necessary to inspect all the hot spots to reduce the uncertainty to an acceptable level. Should it not be good enough to inspect 80% if the acceptable probability of significant corrosion is 0.2?

$$\text{Acceptable probability} = \frac{\text{inspected hot spots}}{\text{number of available hot spots}} \qquad \text{number of available hot spots} < 50??$$

As already mentioned, Bayesian updating is based on the use of a likelihood function and the prior distribution. When using this updating based on new information, one may forget an important aspect: does this new information fit into the first assumed models, or does some of the information indicate that your models are absolutely wrong or misleading? If updating is done without checking the assumptions, important information may be lost. As Aven (2010) writes: "*In many cases, though, new information requires a rethinking of the whole information basis including the uncertainty assessments and the modelling, and Bayes' theorem is not appropriate.*"

This may happen when it is suddenly discovered that a group of hot spots in the corrosion group is very different from the rest; maybe those hot spots should be divided into another corrosion group. If the updating process is being followed without paying attention to the assumptions and the available knowledge before inspection, valuable information may be lost.

Another issue which may be addressed as a challenge when using Bayesian updating, is the need for a knowledge-based probability. Someone may claim that this probability is difficult to assess, and that the numbers are arbitrary if produced by persons without statistical training. On the other hand, Jennifer Lynn Lee has written a very interesting master thesis about *Bayesian Reasoning Method for Intelligence Using Natural Frequencies.* She discusses the benefits of using Bayesian reasoning and argues that it is not difficult for people to assess probabilities as long as they are presented in a way which is natural and known.

She says that: "*Natural frequencies are a way of representing statistical information in a way that people without a strong mathematical background can understand.*" Furthermore, she argues that it is easier to understand 10 out of 100, than 10 percent, based on the fact that 10 out of 100 has a reference to a population, while 10 percent is a base rate. She also receives support for her statement from Leda Cosmides and John Tooby from the Center for Evolutionary Psychology at the University of California, Santa Barbara. They have done some research which shows that natural frequencies are advantageous because they preserve "*important information that would be lost by conversion to a single-event probability*.", Cosmides and Toby (1996). I see this as similar to assessing probability with reference to a standard, like drawing a particular ball out of an urn.

Chapter 3 has presented an example of how Bayesian updating can be used as decision support when doing inspection management. Sections 3.3 and 3.4 have presented the benefits and challenges when using this method. The following chapter, Chapter 4, will present a discussion of the use of Bayesian updating and the introduction of an extended RBI analysis.

CHAPTER 4

DISCUSSION

The use of Bayesian updating represents a strong tool for the combination of background knowledge and new information. Still, it may be a challenge to make sure that these numbers are used as decision support and not treated as the “truth”. Bayesian updating in combination with an evaluation of the different uncertainty factors will secure a systematic treatment of both new information and the uncertainty factors that are often forgotten.

After performing an RBI analysis, and preferably an extended RBI analysis, including an evaluation of the uncertainty factors, Bayesian updating can be used to find the number of inspected hot spots in a corrosion group, and sensitivity studies regarding the different uncertainty factors can be performed, making it possible to check how the different uncertainty factors may influence the number of inspection points in the corrosion group.

In this thesis, the use of Bayesian updating is based on the classification of different corrosion groups. Assuming that different areas belong to a specific corrosion group introduces an uncertainty factor. In some situations this uncertainty factor may have a high degree of uncertainty, due to lack of experienced, new equipment and so on. In other situations, the classification of corrosion groups is clear; there is a lot of relevant data, research, experience and so on. Still, it is important that this uncertainty factor is evaluated; if found important it should be presented and communicated to the management. The number of inspection points found from the use of Bayesian updating should be communicated and presented in combination with an evaluation of uncertainty factors.

Corrosion groups are nothing new in the inspection management process, and dividing hot spots into corrosion groups is normally not problematic. It requires insight into the performance of the piping and how different factors influence corrosion. Even though the process of dividing different areas into different corrosion groups has been done for many years and a lot of experience exists, mistakes can still happen. It is therefore important to evaluate the feedback from inspection and to re-evaluate assumptions if the output from the inspection is different from what was expected.

Furthermore, all uncertainties can not be addressed by probabilities. Uncertainty regarding the fraction of hot spots with significant corrosion can be described using probabilities. The probability is found conditioned on the background knowledge, which may conceal important uncertainty factors, if not identified and communicated. There is therefore a need for an extended risk-based inspection analysis which includes an evaluation of the different uncertainty factors. Including a systematic treatment of uncertainty factors, also using Bayesian updating to check the sensitivity, may reduce the possibility for surprises. An example of the importance of evaluation of uncertainty factors, which is relevant for this thesis, is the inspection method. This thesis has a focus on the number of inspected hot spots, but if something is wrong with the inspection method, performance, equipment and so on, we will not get very far and there will be no need to perform Bayesian updating. It is therefore also necessary to evaluate the uncertainty factor related to the assumption of suitable inspection methods and experienced inspectors.

Dividing the hot spots into different corrosion groups requires a high degree of knowledge about the different corrosion mechanisms. Still, even though a lot of research has been done on corrosion, there is still uncertainty regarding the state of different piping. These uncertainties can have different backgrounds; maybe the parameters in the piping have changed, the piping has been damaged due to external accidents or maybe something unforeseen has happened. Inspections are also performed to check for factors like this, but these uncertainties are difficult to express by probabilities. The need to look beyond probabilities is therefore also present when doing inspection planning; see Aven (2010). There is a danger in overlooking surprises when only focusing on probabilities.

The use of prior distribution should also be discussed; frequentists will argue that the use of prior distribution is based on subjective judgements and should be avoided. As an answer to this I refer to Iversen (1984, pp. 66-67) and other Bayesians who remind us that the use of classical statistics is also subjective to some degree, like the choice of significant level when determining whether or not a null hypothesis should be rejected.

Another aspect is the fact that different priors may lead to different posteriors, at least as long as the number of new data is small, but this is not a new problem. People are daily arguing about the result of different research, they are interpreting the data differently due to their different prior knowledge. Iversen (1984) uses a good example, the main point of which is as follows:

> *A Democrat and a Republican are faced with the same unemployment figure: The Democrat says that the figure shows we need more government involvement, while the Republican argues that the private sector is doing well and will be able to solve the problem.*

This is an honest disagreement in which the difference is in the prior knowledge and opinion, not in the new data represented by the unemployment figure. The prior knowledge should not be hidden, and when deciding the prior distribution this knowledge should be clarified and different assumptions can be checked using a sensitivity analysis.

It is a lot easier to discuss the prior knowledge, asking whether some information has been forgotten or given too little weight, than it is to discuss some produced numbers. Iversen states that when forced to express personal knowledge (opinion and biases) in the prior distribution, the analysis becomes less subjective. I will have to say that I agree; in theory everyone should end up with the same posterior distribution if their background knowledge is the same. This may turn out to be difficult, but should not be seen as a weakness. The main point is to clarify what your analysis is based on, to make sure that your decision process is open and easy for others to understand.

This is also what will be the main advantage of the method presented in this thesis: the need to explain the initial belief and background of the inspection planning. Why is corrosion expected, why do we expect a high fraction of significant corrosion and so on. This will make it easier to communicate why inspection is required and also justify the amount of inspection points. If one can not come to an agreement on the inputs to the analysis, one may use sensitivity analysis to see how the different assumptions influence the posterior distribution; maybe it does not even change the output.

Sometimes the background knowledge is poor and a non-informative prior distribution is chosen, like the uniform distribution presented in Figure 3.7. In some situations this may be a suitable choice, and the numerical values in the posterior distribution will in this case be the same as when using classical statistics. Both the posterior distribution and classical statistics can be used to calculate confidence intervals, and for the uniform prior distribution this will result in the same numerical intervals. **BUT** the interpretation of the interval is completely different and, in my opinion, is also one of the benefits of Bayesian statistics and knowledge-based probabilities.

A 90% confidence interval in classical statistics says that these intervals will contain the parameter, θ (here "real" fraction of significant corrosion) in 90% of the cases in the long run, meaning that you will need a lot of samples and that 90% of the confidence intervals from each of these samples will contain θ. This is a very strange concept, and it is very difficult to understand what this actually means.

A Bayesian credibility 90% interval, on the other hand, is an interval where θ lies between a and b with a probability equal to 0.9, where a and b are numbers. When the Bayesian interval is used to directly assess an observable quantity, it is known as a prediction interval (see Aven, 2010), and can also be specified directly using knowledge-based probabilities. For situations where the sample size is small, a direct assignment of the prediction interval will make more sense than the use of a non-informative prior or classical statistics as these will result in very wide intervals. Observe the new data, and directly assign an interval that has a probability equal for example to 0.9 to contain the parameter or quantity of interest.

Chapter 4.4 in DNV RP G101 (DNV, 2009) divides the RBI method into three: quantitative, qualitative and semi-quantitative/qualitative. In the quantitative model, numerical values can be calculated and traditional classical statistics are used. Next, in the qualitative model an expert judgement is used; the numerical values are assigned not calculated. Further it says: "*However the results are subjective, based on opinions and experience of the RBI team, and are not easily updated following inspection*." This is exactly where the method based on Bayesian updating will come in to use; there will be no use for a distinction between quantitative, qualitative and semi-quantitative/qualitative models, as long as the background knowledge is assessed and the uncertainty factors evaluated.

A probability is assigned, no matter whether it is based on calculations and estimation or knowledge and experience or even a combination thereof. The method in this thesis will make it easier to follow just one method, regardless of the type of the available knowledge. Consequently, it will not be problematic to update the probabilities and the risk after inspections.

CHAPTER 5

CONCLUSION

The use of Bayesian updating as decision support will secure a systematic treatment of new data, and also make sure that all available knowledge can be used: knowledge that can be expressed by expert opinion, historical data, new trends, fraction of hot spots with significant corrosion in similar corrosion groups and so on. Furthermore, the method results in a coherent treatment of the background knowledge with new information, in this procedure represented by new inspection results.

It is important to remember that not all uncertainties can be expressed by probabilities and/or prior distributions, and that there is a need for an evaluation of the different uncertainty factors. A methodology for incorporation of these uncertainty factors has been presented in Section 2.2, and is known as an Extended Risk Based Inspection analysis (ERBI).

The method presented in this thesis is standard Bayesian updating, which can be used as decision support when deciding the number of hot spots that need to be inspected in a large corrosion group.

When introducing the extended risk based inspection methodology, an appropriate weight is given to the different uncertainty factors, and the possibility of surprises can be reduced. The focus on background knowledge and assumptions secures an open and traceable decision process in which it is easy to go back and see what different decisions are based on, and why certain actions have been performed.

Further, when presenting uncertainty factors with a high degree of uncertainty or sensitivity, the management will get the opportunity to perform the necessary judgements and give weight to all relevant aspects in the decision process. It will also be possible to check whether changes in the assumptions result in another risk picture and thereby a different time to next inspection. Important uncertainty factors are not hidden in the analysis, and it becomes the management's responsibility to choose the most suitable decision.

CHAPTER 6

SUGGESTION FOR FUTURE WORK

The method described presented in this thesis is only one application area of Bayesian updating, and may also be used when inspecting to determine the degradation, the deepest corrosion pit or degradation rate.

APPENDIX

Example on Treatment of Uncertainty Factors

When assessing the uncertainty factors, we are interested in the factors which may be able to change the probability of a leak and thereby the time to next inspection. After performing an RBI analysis, the uncertainty has to be evaluated. This section will present another example of how to perform an evaluation of the uncertainty factors, and may be skipped if understood after reading Section 2.2.3.

The first step in the evaluation of uncertainty factors is to find the most important assumptions and identify the different uncertainty factors. Some uncertainties may be partially covered by the use of knowledge-based probabilities in the RBI process. Still, probabilities are not enough to cover all the relevant uncertainty. When assessing probabilities, the probabilities (P) are based on the best available knowledge (K); these probabilities are then conditioned on the background knowledge P(A|K), where A represents the event.

Consequently, as mentioned in Section 2.2.3, there is a need for an assessment of the uncertainty factors which may be “hidden” in the background knowledge. This section will give an example of how some of these uncertainty factors can be treated. The reader is referred to Section 2.2.1 or DNV RP-G101 (DNV, 2009) if unfamiliar with the standard RBI process.

Consider an n-year-old platform where an RBI analysis has been performed. Assume that the RBI analysis is performed using the procedure presented in DNV RP G101 (DNV, 2009), steps 0 – 3 in Figure 2.2. There follows an evaluation of the different uncertainty factors, steps 4 – 6 in Figure 2.2. In some situations, data were insufficient to complete a detailed RBI, and conservative assumptions were made. The RBI analysis is therefore built on several assumptions, some of them more important than others. A list of three assumptions follows:

1. No presence of MIC (microbiological induced corrosion)

2. No CO_2 corrosion

3. The evaluated degradation mechanisms are corrosion and erosion.

The first uncertainty factor addressed is the assumption that there is no presence of MIC. Corrosion problems due to MIC have so far not been reported from earlier inspections. No bacteria analysis/monitoring programme has been performed, and it is unknown whether MIC is a present problem. It is known that seawater is present, and hence there is a possibility of MIC. MIC may occur if the sulphate removal package

(SRP) does not work as intended. However, due to the fact that there have been no earlier problems with MIC, it is disregarded.

The second assumption of no CO_2 corrosion is built on another assumption, that the gas is dry. Even though the water dew point temperature for the hydrocarbon gas is well below the normal operating temperature, condensation can occur in low points and dead legs. Condensation may also occur in the case of shutdown and other abnormal operations. This represents the second uncertainty factor, that the gas actually is dry and hence no CO_2 corrosion.

The third uncertainty factor to be addressed is the assumption that all degradation is due to corrosion and erosion. Fatigue is not considered as no good detailed methods for assessing fatigue exist. The third uncertainty factor is then related to the presence and criticality of fatigue.

The first step in the uncertainty analysis is now performed: to identify the different uncertainty factors. The next step is then to assess and categorize the degree of uncertainty and sensitivity attached to these uncertainty factors. The degree of importance can be decided after combining the degree of uncertainty and sensitivity, and is presented in Table A.

Table A Uncertainty assessment

Uncertainty factor	**Degree of uncertainty**	**Degree of sensitivity**	**Degree of importance**
Presence of MIC	High	High	High
Presence of CO_2	Medium	High	Medium - High
Presence of other degradation mechanisms than corrosion and erosion	High	Medium	High - Medium

The sensitivity is found by looking at the uncertainty factors' possibility to change the time to next inspection. If MIC actually is present, it would have a high influence on the time to next inspection. The occurrence of fatigue may also be able to change the time to next inspection, as occurrence of fatigue under severe conditions (cyclic stress) happens fast and with a high consequence.

Further, it is important to communicate the uncertainty factors with a high degree of importance. Uncertainty factor one has a high degree of importance and should be prioritized when communicating with the management.

After communicating and presenting the important uncertainty factors, is it up to the management to make the final inspection plan. If they find some of the uncertainty factors to be very important, they may ask for further analysis or testing. In this example, they may want to install a bacteria monitoring programme to be able to detect bacteria at an early stage and prevent MIC before it occurs.

Managerial review and judgment are important, as these are the people making the decisions. When making inspection plans, an RBI analysis is used as support. Table A will act as additional decision support in the ERBI analysis work. This gives a systematic treatment of the different uncertainty factors and makes sure that the management has all the available knowledge. Even in situations where the assumptions that are used are conservative, it is up to the management to judge and make decisions. The results from Table A may also be used in a Failure Modes, Effect and Criticality Analysis (FMECA) process, in which additional columns regarding the uncertainty factors and their importance are added. See Aven (2008) for a description of an FMECA analysis, also referred to as FMEA (Failure Mode and Effect Analysis).

In some situations very conservative assumptions may lead to high inspection costs. Uncertainty factors introduced by these assumptions may have a high degree of uncertainty and sensitivity, but will not result in any higher risk. This is due to the fact that even though the uncertainty factor has the possibility to change the time to next inspection, it will only result in a later inspection date.

Uncertainty factors leading to a higher risk picture are of most importance, but uncertainty factors which come from very conservative assumptions may lead to higher inspection costs and, in some situations, these costs may become in gross disproportion to the benefits (ref. ALARP). The main point with evaluating the different uncertainty factors is to make sure that the important factors are presented and communicated to the management.

In some situations these important uncertainty factors are related to very conservative assumptions, and it should be up to the management to decide whether these uncertainty factors are acceptable or not. It is up to the management, and not the team who perform the RBI analysis, to decide whether the costs of the extra inspections can be justified.

Step 6 in Figure 2.2, management review and judgement, needs to reflect the fact that decision making under uncertainty has to balance different concerns, like risk, cost, reputation and so on.

REFERENCES

1. API 2002. *RP 580 – Risk Based Inspection*. 1st ed. American Petroleum Institute.

2. Aven, T. 2003. *Foundations of Risk Analysis.* John Wiley & Sons, Ltd, Chichester, England.

3. Aven, T. 2004. *Risk analysis and science.* Int j of reliability, Quality and Safety Engineering 2004, 11: 1-15.

4. Aven, T. 2008. *Risk Analysis Assessing Uncertainties beyond Expected Values and Probabilities.* John Wiley & Sons, Ltd, Chichester, United Kingdom.

5. Aven, T. 2010. *Misconceptions of Risk.* John Wiley & Sons, Ltd, Chichester, United Kingdom.

6. Aven, T. and Eidesen, K. 2007. *A predictive Bayesian Approach to risk analysis in health care.* BMC Medical Research Methodoloy 2007, 7: 38.

7. Aven, T. and Kvaløy J.T. 2002. *Implementing the Bayesian paradigm in risk analysis.* Reliability Engineering and System Safety; 78: 195-201.

8. Bernardo, J. and Smith, A. 2000. *Bayesian Theory*, John Wiley & Sons, Ltd, Chichester.

9. Cosmides, L. and Tooby, J. 1996. *Are humans good intuitive statisticians after all? Rethinking some conclusions from the literature on judgment under uncertainty.* Cognition 58 (1996) 1-73.

10. DNV 2009. *Recommended practice DNV-RP-G101 - Risk Based Inspection of Offshore Topsides Static Mechanical Equipment*. Det Norske Veritas (DNV), Høvik, Norway.

11. Flage, R. and Aven, T. 2009. *Expressing and communicating uncertainty in relation to quantitative risk analysis (QRA).* Reliability and Risk Analysis: Theory Applications, **2**, 9-18.

12. Geary, W. 2002. *Risk based inspection: A case study evaluation of onshore process plant*. [Online 2011-04-26], Available at: http://www.hse.gov.uk/research/hsl_pdf/2002/hsl02-20.pdf

13. Ghosh, J.K., Delampady, M., Samanta, T., 2006. *An Introduction to Bayesian Analysis, Theory and Methods.* Springer Science+Business Media, LLC, New York, USA.

14. Herzog, B.O. and Jackson, P. 2009. *The ladder to success: Risk-based inspection reduces costs*. *ABB Review* [the corporate technical journal of the ABB group], 1, 30-33.

15. ISO 2002. *Risk Management Vocabulary.* ISO/IEC Guide 73.

16. Iversen, G. 1984. *Bayesian Statistical Inference*. Sage Publications, Inc. California, USA.

17. Lee, J. L. 2007. *Bayesian Reasoning Method For Intelligence Using Natural Frequencies.* Master Thesis Mercyhurs College Erie, Pennsylvania.

18. Lindley, D.V. 1985. *Making Decisions.* John Wiley & Sons, Ltd, London, England.

19. Lord Cullen (The Hon) 1990. The Public Inquiry into the Piper Alpha Disaster. HMSO: London.

20. Røed, W. and Aven, T. 2009. *Bayesian approaches for detecting significant deterioration.* Reliability Engineering and System Safety 94, 604-610.

21. Selvik, J.T. and Aven, T. 2011. *A framework for reliability and risk centred maintenance.* Reliability Engineering and System Safety 96, 324-331.

22. Selvik, J.T., Scarf, P., Aven, T. 2011. *An extended methodology for risk based inspection planning.* Reliability and Risk: Theory & Application; 1 (20):115-125.

23. Simpson, J. 2007. *The application of risk based inspection to pressure vessels and above ground storage tanks in petroleum fuel refineries*. Presented at the Fifth Australasian Congress on Applied Mechanics (ACAM 2007), Brisbane, Australia.

24. Singpurwalla, N.D. 2006. *Reliability and Risk – A Bayesian Perspective.* John Wiley & Sons, Ltd, Chichester, England.

25. Targoutzidis, A. 2010. *The effectiveness of Bayesian updating in dynamic and complex systems*. Journal of Loss Prevention in the Process Industries 23 (2010) 492-497.

26. Vinnem, J. E. 2008. *Risk analysis and risk acceptance criteria in the planning processes of hazardous facilities—A case of an LNG plant in an urban area*. Reliability Engineering and System Safety [e-journal] 95 (662-670) Available through: ScienceDirect. [Accessed 8 October 2010].